

Procrastination in the Field: Evidence from Tax Filing ^{*}

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Abstract

This paper attempts to identify present-biased procrastination in tax filing behavior. Our exercise uses dynamic discrete choice techniques to develop a counterfactual benchmark for filing behavior under the assumption of exponential discounting. Deviations between this counterfactual benchmark and actual behavior provide potential ‘missing-mass’ evidence of present bias. In a sample of around 22,000 low-income tax filers we demonstrate substantial deviations between exponentially-predicted and realized behavior, particularly as the tax deadline approaches. Present-biased preferences not only provide qualitatively better in-sample fit than exponential discounting, but also have improved out-of-sample predictive power for responsiveness of filing times to the 2008 Economic Stimulus Act recovery payments. Additional experimental data from around 1100 individuals demonstrates a link between experimentally measured present bias and deviations from exponential discounting in tax filing behavior.

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1 Introduction

Present-biased preferences (Laibson, 1997; O’Donoghue and Rabin, 1999, 2001) are critical for understanding deviations from the neo-classical benchmark of exponentially discounted utility (Samuelson, 1937; Koopmans, 1960). Prominent anomalies such as self-control problems, the demand for commitment devices, and procrastination in task performance revolve around the tension between long-term plans and short-term temptations inherent to these models.

Identifying present-biased preferences from field data faces a natural challenge. Though the forces of short-term temptations may be observed in behavior, researchers will rarely have access to data on long-term plans.¹ This paper presents a potential way to identify present-biased preferences from field data. Our environment is the often-discussed problem of procrastination in tax-filing (Slemrod et al., 1997; O’Donoghue and Rabin, 1999).² Linking techniques from structural estimation of dynamic discrete choice (Hotz and Miller, 1993; Arcidiciano and Ellickson, 2011) to empirical strategies from public finance (Chetty et al., 2011), we propose a ‘missing mass’ method for identifying deviations from exponential discounting in tax filing behavior. Present-biased procrastination is potentially identified if true filing close to the tax deadline substantially exceeds counterfactual exponential filing.

Differentiating procrastination from optimal delay in the context of tax-filing is notoriously difficult. First, Internal Revenue Service data generally only provides the date which the tax return is processed and not the date of filing (Slemrod et al., 1997; Benzarti, 2015).³ Second, if costs of filing

¹It is potentially for this reason that the body of evidence in support of present-biased preferences comes largely from laboratory study. See Frederick et al. (2002) for a review of the literature and Sprenger (2015) for recent discussion. When field data are used, the arguments in support of present-biased preferences are often calibrational, suggesting that implausibly high levels of discounting would be required to rationalize an observed data set (see, e.g., Fang and Silverman, 2009; Shapiro, 2005); that exponential discounting provides substantially worse fit than a present-biased alternative (see, e.g., Laibson et al., 2005); or sidestep the necessity of having both plan and behavior by providing smoking-gun evidence of sophisticated present bias in the form of commitment demand (see, e.g., Ashraf et al., 2006; Ariely and Wertenbroch, 2002; Bisin and Hyndman, 2014; Kaur et al., 2010; Gine et al., 2010; Mahajan and Tarozzi, 2011). Laibson (2015) provides a recent discussion on the calibrational plausibility of commitment demand in the presence of uncertainty and commitment costs, indicating that commitment may be the exception rather than the rule in many settings.

²Slemrod et al. (1997) coined the phrase ‘April 15th Syndrome’. O’Donoghue and Rabin (1999) use tax filing as their leading example of procrastination predicted by dynamic inconsistency.

³Slemrod et al. (1997) use the 1998 Internal Revenue Service Individual Model File of 95,000 tax returns for the 1988 tax year appended with the date assigned by the IRS Service Center upon receipt. Reference is subsequently

are stochastic, one should expect to see heterogeneous filing times as well as increased filing close to the deadline as the option value of future filing diminishes (Slemrod et al., 1997).⁴ Hence, increased filing close to the deadline is not sufficient to identify procrastination. This project overcomes these issues by using precise data on tax return initiation and filing dates at community tax centers, and by explicitly recognizing stochastic costs in the construction of our exponential benchmark. Further, we link our estimates with both responses to changing filing incentives and experimental measures of time preferences to provide external validation for our interpretation of present-biased procrastination.

In a sample of 22,526 low-income tax filers in the City of Boston from 2005 to 2008, we identify a substantial missing mass in filing behavior relative to an exponential benchmark. Despite a high degree of estimated impatience under exponential discounting, we document a wide deviation between actual and predicted filing probabilities as the end of the tax season approaches. These deviations deliver a missing mass of around 80% additional tax filers relative to the exponential benchmark in the last seven days prior to the deadline.

We interpret our missing mass as evidence of present-biased procrastination in filing and bolster this interpretation with three pieces of evidence. First, alternative rationalizations for the missing mass such as unaccounted-for costs or shocks yield implausible, extreme parameters. Conversely, the data can be rationalized with a relatively small degree of present bias. This gives calibrational support to our interpretation. Second, within our sample period lies the 2008 Economic Stimulus Act, which generated plausibly exogenous variation in filing benefits for 2008 Stimulus Payment

made to the date of processing throughout the text and more than 25% of returns occur in the second half of April (April 17th was the deadline in 1989). Note is made of the potential for IRS delays in assigning dates for returns received during ‘the last-minute surge of filings in April’ (p.698). Slemrod et al. (1997) make use of the 1979-1988 Statistics of Income Panel to conduct longitudinal analysis. The process date is not available in this panel so they use the week at which the return was posted to the IRS Individual Master File and note that the median posting is beyond the tax filing deadline, but that substantial correlation exists between the posting weeks and the process dates. Benzarti (2015) also makes use of the Statistics of Income Panel posting dates and relates them to itemized deductions. As alluded to by Slemrod et al. (1997), a non-standard measurement error problem may be generated if one wishes to use IRS process or posting dates as a proxy for filing times. The correlation between filing dates and process dates is likely influenced by the number of filers. Hence, the concordance between the true measure and the proxy changes through time and is likely worst close to the deadline.

⁴Slemrod et al. (1997) explicitly notes the potential importance of stochastic costs in rationalizing the observed distribution of filing behavior including both heterogeneity and late filing. Though the authors term late filing behavior ‘procrastination’ they note explicitly that their rationalization is dynamically consistent.

recipients.⁵ If individuals were as impatient as our exponential estimates imply, they should exhibit no response to these additional filing benefits. In contrast, difference-in-difference estimates suggest stimulus recipients file around 2 days earlier under the stimulus, a sensitivity that is well predicted out-of-sample by our estimated degree of present bias. Third, we have access to a sub-sample of 1114 individuals who completed incentivized time preference experiments in 2007 and 2008. This sample allows us to link experimental measures of present bias to deviations from exponential discounting in tax filing behavior. The gap between predicted and actual filing behavior correlates strongly with our experimental measures. Present-biased subjects file disproportionately later than exponential prediction relative to other experimental subjects, and this difference is most pronounced towards the end of the tax filing season.

We believe the methods implemented and the results obtained in this paper contribute to several strands of literature in behavioral economics and the broader field.

First, our methods show a path forward for identifying behavioral anomalies in field behavior by implementing structural estimation of a specific, neoclassical model to construct the counterfactual benchmark. A growing body of empirical projects identify behavioral forces using measures of missing mass relative to a traditional atheoretic benchmark such as a smooth or unchanging distribution of behavior (see, e.g., Rees-Jones, 2013; Benzarti, 2015; Allen et al., Forthcoming). In many cases, such as ours, researchers may be interested in rejecting a specific model of behavior rather than a class thereof. Using theory and structural techniques to guide counterfactual construction expands the scope of such missing mass techniques.⁶

Second, and related to the point above, once a single counterfactual model of behavior is rejected, many candidate theories may arise to ‘rationalize’ the missing mass. As carefully demonstrated by Einav et al. (2016) for the case of bunching estimators, different candidate theories could make dramatically different predictions for responsiveness to key policy variables. Assessing the predictive validity of our favored candidate theory by examining responsiveness to the exogenous changes in

⁵It should be noted that the timing of the 2008 Stimulus Payments did not depend on the timing of tax-filing. However, in the advertisement of the program, the IRS clearly conveyed linkages between tax filing timing and Stimulus Payment receipt. See section 2.2 for discussion and details.

⁶Section 3.3 provides additional discussion of these points

filing incentives induced by the 2008 Stimulus Payments is a key contribution of this paper. Such out-of-sample steps are particularly important to take if candidate theories are behavioral, as appeal to additional free parameters in behavioral models will necessarily deliver greater in-sample fit. DellaVigna et al. (Forthcoming) provides one recent demonstration of the value of such out-of-sample tests for behavioral models of reference dependence in the context of job search.⁷

Third, we use experimental measures of time preferences to validate our interpretation of present bias in tax filing. Importantly, our experimental measures come from choices over time-dated monetary payments. A growing discussion in the behavioral literature has questioned the use of such measures given the fungibility of money (Cubitt and Read, 2007; Chabris et al., 2008; Andreoni and Sprenger, 2012; Augenblick et al., 2015; Carvalho et al., 2016; Dean and Sautmann, 2016). Our findings illustrate that such measures may indeed be informative of true preferences given that they relate to apparent procrastination in filing behavior. This also complements the recent contributions of Mahajan and Tarozzi (2011), who show that experimentally elicited preference measures can be productively incorporated into structural approaches in this domain.⁸

Fourth, our paper delivers potentially policy relevant measures of procrastination for the low-income population in question. As noted above, distinguishing procrastination from optimal delay can be extremely difficult. With our credible estimates of present bias we can identify those individuals that are more likely to have procrastinated than not prior to the day they file. Given the aggregate preference estimates, we calculate that on the day of filing, twenty-one percent of filers planned to have filed previously with higher probability than their present-biased behavior delivered. Such potential procrastination is exacerbated at the end of the tax season with roughly seventy-one

⁷DellaVigna et al. (Forthcoming) examine exit from unemployment under reference-dependent preferences and show their preferred model not only rationalizes job finding hazard rates better than a standard model but also provides improved prediction for responsiveness to changes in the structure of unemployment insurance benefits. DellaVigna et al. (Forthcoming) also include a second behavioral parameter beyond reference dependence in the form of present bias. Their estimation strategy of assuming full naivete for this exercise inspired our own. See section 4.2 for detail.

⁸Mahajan and Tarozzi (2011) incorporate experimental measures for time inconsistency, beliefs about disease infection, and purchase and treatment decisions for insecticide treated bednets to estimate the extent of present bias and ‘sophistication’ thereof. In their setting the experimental measures are used directly in estimation, while in ours they are used for validation ex-post. One point noted by Mahajan and Tarozzi (2011) is that in their case the experimental measures themselves wind up having limited predictive power for estimates of present bias that result from their structural exercise.

percent of filers in the final week of the tax season being potential procrastinators. If such widespread procrastination is indicative of behavior when accessing other government services relevant for many low-income individuals, there may be valuable policy dollars spent in altering the timing of costs and benefits of government assistance.

The paper proceeds as follows: section 2 describes the data and the experimental procedures. Section 3 then presents our empirical design and the construction of our missing mass measures. Section 4 presents results, and section 5 concludes.

2 Data

Our exercise makes use of three key data sources: 1) tax filing data from the City of Boston, Massachusetts; 2) variation in tax refunds due to the 2008 Stimulus Act; and 3) experimental measures of time preferences from tax filers in 2007 and 2008.

2.1 Tax Filing Data

The data in this paper comes from 22 Volunteer Income Tax Assistance (VITA) sites in Boston, Massachusetts from the years 2005 to 2008. VITA sites are organized by the City of Boston and the Boston Tax Help Coalition. VITA sites provide free tax preparation assistance to low-to-moderate income households in specific neighborhoods in order to help them claim valuable tax credits such as the Earned Income Tax Credit (EITC). Boston's VITA sites began in 2001 and continue to present. As of the 2015 tax filing season there were 27 VITA sites in operation around the city, processing a total of 12,940 returns and securing around \$22.8 million in refunds of which \$8.6 million were EITC payments (see bostontaxhelp.org for current information and details).

VITA sites generally open in mid-January and close at the tax filing deadline around April 15. Most sites have specific days and hours of operation, though some are open by appointment only. Potential filers are encouraged to bring all required documentation (photo ID, W2 forms, 1099 forms, etc.) to the VITA site. Sites have an in-take coordinator who provides filers with a check-list of

required documents. Filers are usually processed on a first-come, first-served basis and waiting times at popular sites can be substantial during busy periods. Upon reaching the front of the queue, the tax-filer meets with a volunteer preparer, the return is entered, and subsequently filed with the Internal Revenue Service electronically.

In 2005 and 2006 we have access to the date the return was electronically filed, while in 2007 and 2008 we have both the date the return was initiated and the date the return was filed. Around 80% of returns in our final sample are filed within two days of initiation in 2007 and 2008, delivering a close correspondence between when returns are initiated and when they are electronically sent to the IRS. As the deadline approaches, the correspondence grows, with around 90% of returns filed within two days of initiation during the last week of the tax season.⁹ Critical for the present study, we are able to observe the full return information including the date each return was initiated and/or electronically filed, whether any refund would be received via direct deposit or paper check, and the size of federal refunds.

From 2005 to 2008 a total of 32,641 tax returns were initiated at VITA sites. Of these, 26,040 (87.6%) were filed electronically with documented acceptance by the IRS in our data.¹⁰ To have the most precise measure possible for when individuals decide to file, we use the electronic filing date from 2005-2006 and the initiation date from 2007-2008 as our measured filing date. We recognize that the 2005-2006 filing times may slightly overstate the timing of tax filing relative to 2007-2008, and so also provide all estimates using only the latter years for which precisely measured initiation data are available¹¹.

We restrict the sample along several other dimensions for our study of procrastination. First, we remove 212 (0.8%) individuals who have filing dates after the filing deadline. Second, we focus on only the 11 weeks prior to the deadline such that the majority of subjects can be expected to

⁹The mean (median) filing lag for 2007 and 2008 is 2.3 (0) days, and in the last week of the tax season the mean (median) filing lag is 0.8 (0) days.

¹⁰28,606 returns were ever sent to the IRS. Of these 2215 (7.7%) returns have a documented rejection. Though many of these returns were subsequently filed and accepted, our data have the initial electronic filing date overwritten by the subsequent filing. For a further 352 (1.2%) returns, we have no documented acceptance. We are hesitant to use these data as we are unsure either of the first filing date or of when, if ever, a refund was received.

¹¹To to this end, we reproduce our primary estimation results, shown in table 2, with only 2007 data. The results can be found in appendix table A2

have received their primary tax documents such as W2's.¹² This eliminates 621 (2.4%) observations. Third, we focus only on subjects with weakly positive refunds, eliminating a further 1457 (5.6%) filers.¹³ Fourth, we eliminate 1174 (4.5%) individuals with zero dollars of taxable income and zero dollars of refund. Such individuals would not generally need to file taxes, but do so likely because of the 2008 Stimulus Payments which provided rebates to such filers.¹⁴ Fifth, a small number of subjects, 65 in total, appear to file on Sundays when VITA sites are generally closed and no electronic filing should be possible. We believe these special cases correspond to appointments or VITA site workers filing on their own behalf and, hence, drop these observations as well. In total, these restrictions eliminate 13.5% of observations leaving a usable sample of 22,526 individual tax filings.

Table 1, Panel A presents summary statistics for our sample across the four years of our study. Tax filers are around 38 years old, earn around \$17,000 in adjusted gross income, and receive sizable federal refunds of around \$1,400. Tax filers have slightly more than half a dependent, and around 10% of subjects receive unemployment benefits in any given year. In addition to the above measured socio-demographics which are captured directly from tax returns, VITA sites also ask tax-filers to complete a socio-demographic survey to identify gender, race, and education levels. Response rates for these questions vary from 77% to 78%. Panel B demonstrates that conditional on responding, the majority of tax filers report they are female, African-American, and without college experience.

Table 1, Panel C presents two important time related variables: the number of days until the filing deadline and whether or not a tax-filer opts to receive their refund by direct deposit. In order to identify the number of days until the tax filing deadline we subtract the deadline date from the filing date. On average filing occurs 44 days before the tax filing deadline with substantial heterogeneity. Individuals who receive their refund by direct deposit can expect to receive their refund substantially

¹²Our empirical exercise will require individuals to project whether individuals with similar characteristics will file in the next period. Including the relatively sparse data outside of 11 weeks, generates some missing or extreme projections.

¹³Because tax filers have relatively low incomes, they generally receive substantial proportional refunds associated with the EITC and other tax credits. Our empirical exercise estimates an optimal stopping problem with costs of filing and refund benefits. We do not explicitly model the kink in incentives associated with filing beyond the deadline and incurring a tax penalty if one has a negative refund. With negative refunds, individuals will have incentives primarily to file close to the deadline.

¹⁴Indeed, 906 of 1174 (77.2%) individuals who fall into this category are observed in 2008.

earlier than those who do not. Given that only 40% of our sample opts for direct deposit, this presents potentially important cross-sectional variation in the timing of refund receipts.¹⁵

Table 1: Summary Statistics

<i>Panel A: Tax Return Information</i>			<i>Panel B: Demographics:</i>			<i>Panel C: Filing and Direct Deposit</i>		
Variable	Obs	Mean (s.d.)	Variable	Obs	Mean (s.d.)	Variable	Obs	Mean (s.d.)
Age	22524	37.87 (15.54)	Female (=1)	17541	0.648 (0.48)	Days until Deadline	22526	44.06 (21.68)
Adjusted Gross Income	22526	16924.8 (13367.2)	Black (=1)	17268	0.560 (0.50)	Direct Deposit (=1)	22526	0.397 (0.49)
Federal Refund	22526	1419.82 (1618.2)	College Experience (=1)	16757	0.155 (0.36)			
# Dependents	22526	0.535 (0.87)						
Unemployed (=1)	22526	0.095 (0.29)						

Notes: Summary statistics for refund recipients with electronic filing at Boston VITA tax centers between 2005 and 2008. Panel A and Panel C data collected from individual tax returns. Panel B data collected from voluntary demographic survey.

2.2 Economic Stimulus Act 2008

A key component of our exercise attempts to predict sensitivity of filing behavior to the exogenous change in filing incentives provided by the Economic Stimulus Act of 2008. Under the Economic Stimulus Act of 2008 (H.R. 5140) passed on February 7, 2008, tax filers earning less than \$75,000 (\$150,000 for joint filers) received ‘Recovery Rebates’ between \$300 and \$1200, depending on filing status and income levels. The Stimulus Payments were announced in February 2008. In practice, these payments were generally disbursed between late April and July of 2008 depending on the social security number of the tax filer. In 2008, 90% of the filers we observe qualified to receive Stimulus Payments. Appendix Figure A1 presents the histogram of Stimulus Payments calculated

¹⁵Each year (through 2012) the IRS provided tax-filers with a refund cycle linking electronic filing and acceptance dates to dates when direct deposits would be sent and paper checks would be mailed. In general, accepted returns are batched by week and paper checks are mailed one week after direct deposits are sent. For our baseline estimate we ignore the discontinuities in refund receipt induced by this batching protocol as it is unlikely that tax-filers in our sample would have access to such information. Additionally, the data do not appear to reflect the batch discontinuities with individuals bunching close to batch endpoints.

from individual tax return data.¹⁶

Prima-facie, the 2008 Stimulus Payments, whose values were based on predetermined income and demographics, could provide for exogenous variation in refund sizes and give potential for difference-in-difference investigation across recipients and non-recipients. However, the timing of tax-filing had no true impact on the receipt of the Stimulus Payments and hence did not truly influence the intertemporal tradeoffs. Nonetheless, it is not clear that tax filers at VITA sites, or anyone else for that matter, were aware of this point. The initial February 2008 announcement did not clarify that the timing of Stimulus Payments was decoupled from dates of tax-filing, but noted only that the payments would begin being made in May of 2008.¹⁷ Furthermore, the IRS’ documentation of the Stimulus Payments may have created the impression that Stimulus Payment timing was linked to filing dates. Filers examining the Frequently Asked Questions website related to the Stimulus Payment asking ‘When will I receive my Stimulus Payment?’ were told¹⁸:

Processing times for tax returns and Stimulus Payments vary. If you are getting a regular tax refund, the IRS will send you that refund first. Normally, your Stimulus Payment will follow one to two weeks later.

Such information likely gave filers the impression of a tight link between filing times and Stimulus Payment receipt. The 2008 Stimulus Payments generate plausibly exogenous variation in the benefits of filing. In Section 4.3 we use the 2008 Stimulus Payment data and attempt to predict responsiveness to these changing filing incentives under our estimated preferences out-of-sample.

¹⁶The 2008 stimulus rebate took two forms. The first was allocated according to filing status, tax liability, adjusted gross income, and number of dependents. The second was allocated according to filing status, number of dependents, adjusted gross income, social security, and other qualifying income. The first type was phased in and out according to AGI. Each individual received the larger of the two rebates. The exact formula is detailed in the “Technical Explanation of the Revenue Provisions of H.R. 5140.” Using each individual’s 1040A data we calculated their rebates with python script.

¹⁷Appendix B reproduces the IRS announcement. Additionally, the actual process of payment was not described in the technical description of the Stimulus Payments. Appendix C reproduces the relevant portions of the technical explanation of the revenue provisions of the Economic Stimulus Act of 2008.

¹⁸See <https://www.irs.gov/uac/Economic-Stimulus-Payment-Q&As:-When-Will-I-Get-the-Payment%3F> for details. This website was updated in July 2008 likely to reflect the volume of payment to date.

2.3 Experimentally Elicited Time Preferences

For a subsample of tax filers, we have independent measures of time preferences elicited using experimental methods. In 2007 and 2008 at one VITA site, in Roxbury, MA, we conducted incentivized intertemporal choice experiments throughout the tax filing season. These data are discussed in detail in Meier and Sprenger (2015), which analyzes stability of elicited preferences at the aggregate and individual level.¹⁹ A total of 1906 individuals in our sample received tax-filing assistance in 2007 and 2008 at the Roxbury VITA site. Of these 1,794 filed their taxes on one of the days the experiment was conducted and were eligible to participate. In both years VITA site intake material included identical, incentive-compatible choice experiments to elicit time preferences. The choice experiments were presented on a single colored sheet of paper and were turned in at the end of tax-filing for potential payments (see below). The experimental paradigm is presented as Appendix D. 1300 individuals, (72.5%) elected to participate. Appendix Table A1 presents observable characteristics of our experimental subjects and compares them to the observables of non-participating subjects at the Roxbury VITA site. Experimental subjects appear similar on observables to non-participating subjects.

Individual time preferences are elicited using identical incentivized multiple price lists in both 2007 and 2008 (for similar approaches to elicit time preferences, see Coller and Williams, 1999; Harrison et al., 2002; McClure et al., 2004; Dohmen et al., 2006; Tanaka et al., 2010; Burks et al., 2009; Benjamin et al., 2010; Ifcher and Zarghamee, Forthcoming). Individuals were given three multiple price lists and asked to make a total of 22 choices between a smaller reward, X , in period t and a larger reward, $Y > X$, in period $t + \tau > t$. We keep Y constant at \$50 and vary X from \$49 to \$14 in three time frames. In Time Frame 1, t is the present, $t = 0$, and τ is one month. In Time Frame 2, t is the present, and τ is six months. In Time Frame 3, t is six months from the study date, and τ is again one month. The order of the three time frames was randomized. Appendix D provides the full set of choices.

¹⁹Meier and Sprenger (2015) demonstrate stable choice profiles and corresponding parameter estimates at both levels and a one-year correlation in behavior of around 0.5. Instability in experimental choice is largely orthogonal from demographics or changes in financial situation.

In order to provide an incentive for truthful choice, 10 percent of individuals were randomly paid one of their 22 choices (for comparable methodologies and discussions, see, e.g., Harrison et al., 2002). This was done with a raffle ticket, which subjects took at the end of their tax filing and which indicated which choice, if any, would result in payment. To ensure credibility of the payments, we filled out money orders for the winning amounts on the spot in the presence of the participants, put them in labeled, pre-stamped envelopes and sealed the envelopes. The payment was guaranteed by the Federal Reserve Bank of Boston and individuals were informed that they could always return to the head of the VITA site (the community center director) where the experiment was run to report any problems receiving the payments. Money orders were sent by mail to the winner’s home address on the same day as the experiment if $t = 0$, or in one, six, or seven months, depending on the winner’s choice. All payments were sent by mail to equate the transaction costs of sooner and later payments. The details of the payment procedure of the choice experiments were kept the same in the two years and participants were fully informed about the method of payment.

The multiple price list design yields 22 individual-level decisions between smaller, sooner payments X and larger, later payments Y . We term the series of decisions between X and Y a *choice profile*. We make one restriction on admissible choice profiles: that the choices satisfy monotonicity within a price list.²⁰ Roughly 86% of our sample, or 1114 individuals satisfy this restriction

In order to identify present bias from the observed choice profiles, we examine choices made in Time Frame 1 ($t = 0, \tau = 1$), and Time Frame 3 ($t = 6, \tau = 1$). Let X_1^* be the smallest value of X for which an individual chooses X over Y in Time Frame 1, and let X_3^* be the smallest value of X for which an individual chooses X over Y in Time Frame 3. An individual is coded as *Present-Biased* if $X_1^* < X_3^*$, having expressed more patience over six vs. seven months than over today vs. one month. Similar measures for identifying time preferences from experimental data

²⁰That is, individuals do not choose X over Y and Y over X' if $X' < X$. This restriction is equivalent to focusing on individuals with unique monotonic switch points and individuals without any switch points in each price list. The level of non-monotonicity obtained in our data compares favorably to the level obtained in other multiple price list experiments with college students, where around 10% of individuals have non-unique switch points (Holt and Laury, 2002) and is substantially below some field observations where as many as 50% of individuals exhibit non-unique switch points (Jacobson and Petrie, 2009). For non-monotonic subjects we are unable to have a complete record of their choices as we measure only their first switch point and whether they switched more than once. Price list analysis often either enforces a single switch point (Harrison et al., 2005) or eliminates such observations.

have been employed by Collier and Williams (1999); Harrison et al. (2005); McClure et al. (2004); Dohmen et al. (2006); Tanaka et al. (2010); Burks et al. (2009); Benjamin et al. (2010); Ifcher and Zarghamee (Forthcoming); Meier and Sprenger (2010). Of our 1114 subjects, 360 (32%) are classified as *Present-Biased*.²¹

In Section 4.4, we link this experimental measure of present bias to deviations from exponential discounting in tax filing behavior.

3 Empirical Strategy

Our empirical strategy for identifying deviations from exponential discounting in tax filing has three primary components. First, we construct and estimate a dynamic discrete choice, optimal stopping model for the timing of tax filing. Importantly, this model is estimated under the assumption of exponential discounting. Second, we construct a counterfactual distribution of filing behavior based on the estimated exponential parameters. And third, we identify deviations from the exponential benchmark by statistically comparing realized and counterfactual behavior.

3.1 Tax Filing as Dynamic Discrete Choice

An individual's decision to file taxes can be viewed as an optimal stopping problem. In each period before the filing deadline, the individual decides whether to incur a realized cost and receive the benefit of sooner receipt of their refund, or to wait to file on a future date. Though all individuals in our sample receive positive refunds, and hence face no penalty for late filing, we assume the costs of filing become sufficiently high once the VITA sites close such that no individual ever desires or forecasts filing after the deadline.²² The methodology we implement and the following notation borrows heavily from Hotz and Miller (1993); Arcidiciano and Ellickson (2011).

There are N individual tax filers, indexed by i . Time is discrete, indexed by t , with T denoting

²¹111 (10%) of subjects are classified as *Future-Biased* with $X_1^* > X_3^*$. The remaining 643 subjects (58%) exhibit $X_1^* = X_3^*$ consistent with exponential discounting.

²²In principle, individuals with positive refunds have three years to file and claim their refunds from the IRS. After three years, the funds become the property of the United States Treasury.

the period of the tax deadline. In each period, tax filers take actions a_{it} . They either decide to postpone filing ($a_{it} = 0$) or to file ($a_{it} = 1$). Let f_{it} denote the individual's filing status in period t such that $f_{it} = 1$ if the individual has not yet filed by period $t - 1$ and $f_{it} = 0$ if the individual has filed by period $t - 1$. We assume that each individual will receive a positive refund, b_i , constant through time and known to the researcher and the filer. This refund is to be received in a fixed number of periods, k , after filing. The state variables known to the researcher are $x_{it} = (f_{it}, b_i)$, which is Markov.

We assume that costs of filing have both a fixed and an idiosyncratic component. The fixed costs of filing are denoted by c and the time-varying idiosyncratic shocks are denoted by ϵ_{it} . These shocks are contemporaneously observed by the filer but unobserved to the researcher. These shocks may depend on the choice of filing and hence we write $\epsilon(a_{it})$. We assume $\epsilon(a_{it})$ is independent and identically distributed over time with pdf $g(\epsilon(a_{it}))$. This is an unknown state variable.

Filer utility is additively separable. The utility of filing in period t is

$$\delta^k b_{it} - c + \epsilon(1)$$

when $a_{it} = 1$ and $f_{it} = 1$. The variable δ^k is a k period *exponential* discount factor homogeneous in the population of filers. Utility is $\epsilon(0)$ if $a_{it} = 0$ and $f_{it} = 1$. As such, the flow utility can be written

$$u(x_{it}, a_{it}) + \epsilon_{it}(a_{it}) = a_{it} f_{it} (\delta^k b_i - c) + \epsilon_{it}(a_{it}).$$

With these flow utilities, the filer maximizes the present discounted value of filing-related utilities by choosing α_i^* , a set of decision rules for all possible realizations of observed and unobserved state variables in each time period. That is,

$$\alpha_i^* = \arg \max_{\alpha_i} E_{\alpha_i} \sum_{t=1}^T \delta^{t-1} [u(x_{it}, a_{it}) + \epsilon_{it}(a_{it})].$$

The corresponding value function at time t can be defined recursively as

$$V_{it}(x_{it}, \epsilon_{it}) = \max_{a_{it}} [u(x_{it}, a_{it}) + \epsilon_{it}(a_{it}) + \delta E [V_{i,t+1}(x_{i,t+1}, \epsilon_{i,t+1}) | x_{it}, a_{it}]]$$

We define the *ex-ante* value function, $\bar{V}_{it}(x_{it})$, obtained by integrating over the possible realizations of shocks as

$$\bar{V}_{it}(x_{it}) \equiv \int V_{it}(x_{it}, \epsilon_{it}) g(\epsilon_{it}) d\epsilon_{it}.$$

We additionally define the conditional value function $v_{it}(x_{it}, a_{it})$ as the present discounted value (net of the shocks ϵ_{it}) of choosing a_{it} and behaving optimally from period $t + 1$ on as

$$v_{it}(x_{it}, a_{it}) \equiv u(x_{it}, a_{it}) + \delta \int \bar{V}_{i,t+1}(x_{i,t+1}) f(x_{i,t+1} | x_{it}, a_{it}) dx_{i,t+1}.$$

The optimal decision rule at time t solves

$$\alpha_{it}(x_{it}, \epsilon_{it}) = \arg \max_{a_{it}} v_{it}(x_{it}, a_{it}) + \epsilon_{it}(a_{it}).$$

3.1.1 Type-1 Extreme Value Errors

Following the logic of static discrete choice problems, the probability of observing an action a_{it} conditional on x_{it} is found by integrating out ϵ_{it} from the optimal decision rule.

$$\begin{aligned} p(a_{it} | x_{it}) &= \int \mathbf{1}[\alpha_{it}(x_{it}, \epsilon_{it}) = a_{it}] g(\epsilon_{it}) d\epsilon_{it} \\ &= \int \mathbf{1}[\arg \max_{a_{it}} v_{it}(x_{it}, a_{it}) + \epsilon_{it}(a_{it}) = a_{it}] g(\epsilon_{it}) d\epsilon_{it} \end{aligned}$$

Hence, if we are able to form the conditional value function $v_{it}(x_{it}, a_{it})$, standard methods can be applied.

In order to obtain choice probabilities and other constructs in closed form, we assume a type-1 extreme value distribution, fixing the location parameter equal to minus Euler's constant, $-\gamma =$

-0.5772, and the scale parameter to 1.²³ This leads to a dynamic logit model where the probability of an arbitrary choice a_{it} is given by

$$p(a_{it}|x_{it}) = \frac{\exp(v_{it}(x_{it}, a_{it}))}{\sum_{a'_{it}} \exp(v_{it}(x_{it}, a'_{it}))}.$$

Or,

$$p(a_{it}|x_{it}) = \frac{1}{\sum_{a'_{it}} \exp(v_{it}(x_{it}, a'_{it}) - v_{it}(x_{it}, a_{it}))}.$$

As in the standard logit, the probability of any action being taken is expressed in terms of relative utility values or utility differences. Here, however, the relevant utility values are the conditional value functions. The conditional value functions carry with them both the current flow payoffs and discounted considerations of taking the prescribed action and then acting optimally from then on.

Importantly, under the above distributional assumption we also have the ex-ante value function in closed form.

$$\bar{V}_{it}(x_{it}) = \ln \left[\sum_{a'_{it}} \exp(v_{it}(x_{it}, a'_{it})) \right].$$

A powerful observation by Hotz and Miller (1993) recognizes that

$$\bar{V}_{it}(x_{it}) = -\ln[p(a_{it}^*|x_{it})] + v_{it}(x_{it}, a_{it}^*)$$

²³The cumulative distribution function of a type-1 extreme value random variable, X , $Prob(X \leq x) = F(x; \mu, \lambda) = e^{-e^{-(x-\mu)/\lambda}}$, is summarized by location parameter, μ , and scale parameter, λ . The expectation is

$$E[X] = \mu + \gamma\lambda,$$

such that fixing location $\mu = -\gamma$ and $\lambda = 1$ ensures the shocks are mean zero. In most situations, imposing mean zero shocks is inconsequential as choices are driven by the *difference* between action-specific shocks. In period T , however, the individual must file if she has not yet, and so in period $T - 1$ the individual forecasts only one relevant shock in the subsequent period. Additionally, in all prior periods, choosing to file in the period stops the problem and sets all future flow utilities to zero, while choosing not to file exposes the decisionmaker to future shocks. Under the traditional assumption that $\mu = 0$, such future shocks would yield additional option value to not filing in any period. In Appendix Table A3 we re-estimate the specifications of Table 2 with the traditional assumption of $\mu = 0$ and show that estimated discount factors and costs are both slightly reduced under this assumption. Note as well, that the variance of a type-1 extreme value random variable is $\lambda^2 \frac{\pi^2}{6}$, such that restricting $\lambda = 1$ also restricts the variance of the shocks to be $\frac{\pi^2}{6}$. In section 4.1.1 we analyze behavior with alternate assumptions for λ , and ensure that both our estimated model and simulations with $\mu = -\gamma$ and $\lambda = 1$ predict identical behavior.

for some arbitrary action taken at time t , a_{it}^* . This expresses the ex-ante value of being at a given state as the conditional value of taking an arbitrary action adjusted for a penalty that the arbitrary action might not be optimal. We can substitute this in to our equation for the conditional value function to obtain

$$v_{it}(x_{it}, a_{it}) = u(x_{it}, a_{it}) + \delta \int (v_{i,t+1}(x_{i,t+1}, a_{i,t+1}^*) - \ln[p(a_{i,t+1}^* | x_{i,t+1})]) f(x_{i,t+1} | x_{it}, a_{it}) dx_{i,t+1}$$

The components of the conditional value function are contemporaneous flow payoffs, $u(x_{it}, a_{it})$, the one period ahead conditional value function for the arbitrary action, $v_{i,t+1}(x_{i,t+1}, a_{i,t+1}^*)$, conditional choice probabilities for the arbitrary action $p(a_{i,t+1}^* | x_{i,t+1})$, and state transition probabilities, $f(x_{i,t+1} | x_{it}, a_{it})$. These constructs are obtainable in the following ways:

Formulating Contemporaneous Flow Payoffs: The flow payoffs are established as $\delta^k b_{it} - c$ if a person enters period t without having filed and files in that period. The flow payoffs are 0 otherwise. The refund value noted in Table 1, provides the value b_{it} . This refund will be received in k periods with the assumptions that for direct deposit filers, $k = 14$ while for paper check filers $k = 21$.²⁴ The parameters to estimate are the discount factor, δ , and filing costs, c .

Obtaining Conditional Choice Probabilities: We wish to have an estimated probability for a_{it} given the state vector x_{it} . Our states are the benefit amount, b_i , and whether someone has not already filed, f_{it} . These can be calculated with simple bin estimators.

$$\tilde{p}(a_{it} | x_{it}) = \frac{\sum_{i=1}^N \mathbf{1}(a_{it} = a_t, x_{it} = x_t)}{\sum_{i=1}^N \mathbf{1}(x_{it} = x_t)}$$

Obtaining State Transition Probabilities: Our only states are the benefit amounts b_i and the filing

²⁴We follow the IRS refund cycle charts for 2005-2008 to arrive at these values of k .

status f_{it} . The benefit amount is unchanging through time, and conditional upon f_{it} and the choice a_{it} , $f_{i,t+1}$ can be known with certainty. Hence, all the state transition probabilities are 1.

Obtaining Arbitrary Action Payoff from Terminating Actions: Our setup is such that there exist terminating actions. Once a filer files, no further choice can be made. The decision problem is no longer dynamic. This is important because if we think of this terminating action of filing as the arbitrary action, $a_{i,t+1}^*$, then the remaining analysis is dramatically simplified. The terminating action makes all future payoffs zero and makes future shocks irrelevant. Filling in $a_{i,t+1}^* = 1$ as the arbitrary action, we know that the $t + 1$ conditional value function will be

$$v_{i,t+1}(1, b_i, 1) = \delta_i^k b_i - c$$

if $f_{i,t+1} = 1$. Otherwise, the individual has already filed, $f_{i,t+1} = 0$, and this along with all future values are deterministically zero.

3.1.2 Likelihood Formulation

Our primary equation for the value of a given action given a particular state is

$$v_{it}(x_{it}, a_{it}) = u(x_{it}, a_{it}) + \delta \int (v_{i,t+1}(x_{i,t+1}, a_{i,t+1}^*) - \ln[p(a_{i,t+1}^* | x_{i,t+1})]) f(x_{i,t+1} | x_{it}, a_{it}) dx_{i,t+1}$$

The critical case for our estimator is $x_{it} = (f_{it}, b_i) = (1, b_i)$. The individual has not yet filed their taxes and decides between filing today and not filing today. Filing today yields immediate costs and discounted benefits. It also transitions the future filing state to $f_{i,t+1} = 0$, such that all future flow payoffs and the future ex-ante value function is zero. Together these yield

$$v_{it}(1, b_i, 1) = \delta^k b_i - c + \delta \int 0$$

$$v_{it}(1, b_i, 1) = \delta^k b_i - c$$

Now, consider the individual who chooses to not file. Filing today yields zero costs and zero benefits. It advances time, but the state in the future will be $x_{i,t+1} = (1, b_{i,t+1})$ with probability 1. Given this state and the arbitrary action that the individual files, the value of this option is simply calculated as well.

$$v_{it}(x_{it}, a_{it}) = u(x_{it}, a_{it}) + \delta \int (v_{i,t+1}(x_{i,t+1}, 1) - \ln[p(1|x_{i,t+1})]) f(x_{i,t+1}|x_{it}, a_{it}) dx_{i,t+1}$$

$$v_{it}(1, b_i, 0) = 0 + \delta[\delta^k b_i - c] - \delta \ln[p(1|x_{i,t+1})]$$

$$v_{it}(1, b_i, 0) = \delta^{k+1} b_i - \delta c - \delta \ln[p(1|x_{i,t+1})]$$

We can evaluate the difference between these two conditional value functions as:

$$\begin{aligned} v_{it}(1, b_i, 0) - v_{it}(1, b_i, 1) &= \\ [\delta^{k+1} b_i - \delta c - \delta \ln[p(1|x_{i,t+1})]] - [\delta^k b_i - c] &= \\ (\delta^{k+1} - \delta^k) b_i - (\delta - 1) c - \delta \ln(p(1|1, b_i)). \end{aligned}$$

Under the error distribution, we have:

$$p(a_{it}|x_{it}) = \frac{1}{\sum_{a'_{it}} \exp(v_{it}(x_{it}, a'_{it}) - v_{it}(x_{it}, a_{it}))}.$$

Or,

$$p(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp[(\delta^{k+1} - \delta^k) b_i - (\delta - 1) c - \delta \ln(p(1_{i,t+1}|1_{i,t+1}, b_i))]}.$$

This represents the likelihood contribution of observation t for individual i given the decisionmaker has not filed yet. Note that we only need to consider those periods up until the time when the person files. Once they file, the utility consequences of filing are eliminated and the likelihood contribution is zero for such observations. Let D_i be the filing date of a given individual. The grand log likelihood is written as

$$\mathcal{L} = \sum_{i=1}^N \left[\sum_{t=1}^{D_i} \ln[p(1_{it}|1_{it}, b_i)] \right] \quad (1)$$

3.1.3 Identification

From the likelihood of (1), we wish to estimate the parameters δ and c . It is worth noting that exercises of this form suffer generically from identification problems (Rust, 1994). The underlying issue is that monotonic transformations of the instantaneous utility function will yield identical choice rules and hence identical likelihoods. Normalizations and functional form assumptions are often invoked to deliver credible estimates of remaining parameters. One frequent normalization is to assume a specific one period discount factor (Bajari et al., 2007; Kennan and Walker, 2011; Aguirregabiria and Mira, 2007).²⁵

Our environment differs in one compelling way from most exercises in that filing costs and benefits are not experienced in the same period. The fact that $k > 0$ delivers some potential for estimating both δ and c from the data. Naturally, this is in the presence of our additional functional form assumptions and normalizing post-filing payoffs to zero, but without $k > 0$, the identification issues would be severe. In Appendix A.2, we describe this point in detail. We show in (δ, c) space that level sets of conditional filing probabilities for multiple periods tightly overlap when $k = 0$, indicating that many parameter constellations lead to the same probabilistic choice behavior. When $k > 0$, these level sets separate, implying differential intertemporal patterns of probabilistic behavior for different parameter combinations. Of additional note is that for different values of $k > 0$, the same parameters lead to (at times notably) different filing probabilities. Hence, differential direct deposit use, which generates differences in k , delivers additional identifying variation.

²⁵The identification of the discount factor in dynamic discrete choice settings has received substantial theoretical attention. Several potential paths forward have been proposed that are not reliant of functional form for identification. One is using variation that changes transition probabilities but do not change contemporaneous utilities (Magnac and Thesmar, 2002). This technique has been usefully applied by Fang and Wang (2015) and Mahajan and Tarozi (2011) not just for identifying the discount factor, but also for present bias. We are not aware of a variable that can serve such a purpose in our setting.

3.2 Constructing Counterfactuals

Maximum likelihood estimation of the above dynamic discrete logit provides parameter estimates for discounting and the costs of filing, $\hat{\delta}$ and \hat{c} . With these parameters in hand one can construct the counterfactual distribution of filing behavior through backwards induction at the estimated values of $\hat{\delta}$ and \hat{c} ,

$$\hat{p}(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp \left[(\hat{\delta}^{k+1} - \hat{\delta}^k) b_i - (\hat{\delta} - 1) \hat{c} - \hat{\delta} \ln(\hat{p}(1_{i,t+1}|1_{i,t+1}, b_i)) \right]},$$

with $\hat{p}(1_{iT}|1_{iT}, b_i) = 1$. A first natural counterfactual distribution for behavior is the average fitted conditional filing probability,

$$\hat{p}(1_t|1_t) = \frac{1}{N} \sum_{i=1}^N \hat{p}(1_{it}|1_{it}, b_i).$$

This counterfactual distribution could be compared to its empirical analog $\tilde{p}(1_t|1_t)$ to examine the adherence of true and estimated conditional filing probabilities for all periods until period $T - 1$.²⁶ Under the assumptions of the model, exponential discounting and rational expectations, $\hat{p}(1_t|1_t)$ and $\tilde{p}(1_t|1_t)$ should coincide perfectly.²⁷

From the conditional filing probability, $\hat{p}(1_{it}|1_{it}, b_i)$, one can construct additional counterfactuals for other aspects of filing behavior. First, one can construct the probability of filing unconditional on the contemporaneous filing status, f_{it} , as

$$\hat{q}(1_{it}|b_i) = \hat{p}(1_{it}|1_{it}, b_i) \prod_{s=0}^{t-1} (1 - \hat{p}(1_{is}|1_{is}, b_i)),$$

²⁶In period T , the filing probability is assumed to be 1 and all remaining individuals will file by construction.

²⁷An alternative counterfactual that does not rely on backwards induction can also be generated. One simply constructs the fitted probabilities using the bin estimates for future filing probabilities, $\tilde{p}(1_{i,t+1}|1_{i,t+1}, b_i)$, as the future values,

$$\hat{\hat{p}}(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp \left[(\hat{\delta}^{k+1} - \hat{\delta}^k) b_i - (\hat{\delta} - 1) \hat{c} - \hat{\delta} \ln(\tilde{p}(1_{i,t+1}|1_{i,t+1}, b_i)) \right]}.$$

The average fitted value is thus

$$\hat{\hat{p}}(1_t|1_t) = \frac{1}{N} \sum_{i=1}^N \hat{\hat{p}}(1_{it}|1_{it}, b_i).$$

We examine such an alternative and find qualitatively very similar results (see section ?? for details).

and the number and percentage of filers at t as $\sum_{i=1}^N \hat{q}(1_{it}|b_i)$ and $\frac{100}{N} \sum_{i=1}^N \hat{q}(1_{it}|b_i)$, respectively. Additional useful constructs are the expected average refund value at t ,

$$\hat{b}_t = \frac{\sum_{i=1}^N \hat{q}(1_{it}|b_i) \times b_i}{\sum_{i=1}^N \hat{q}(1_{it}|b_i)},$$

and the expected filing date for individual i ,

$$\hat{t}_i^* = \sum_{t=0}^T \hat{q}(1_{it}|b_i) \times t.$$

Our estimator is disciplined by the data in that the probability of filing in a given period is informed by the forecasted conditional filing probability which is correct in expectation. This reliance on rational expectations in estimation allows the estimator to make use of the wealth of expectations information in the data (Arcidiciano and Ellickson, 2011). However, it necessarily entails constructing counterfactual distributions under the joint assumption of rational expectations and exponential discounting.

3.3 Missing and Excess Mass

In order to identify deviations from exponential discounting, the true distributions of behavior must deviate substantially from predicted distributions. That is, exponential discounting must mischaracterize the intertemporal patterns of filing.

Our methodology is similar in spirit to previous research identifying the force of incentives using estimates of missing or excess mass in a true distribution relative to a counterfactual distribution (Chetty et al., 2011; Rees-Jones, 2013; Allen et al., Forthcoming). In prior exercises a smooth counterfactual distribution of behavior is estimated with non-parametric measures such as a n -degree polynomial. These estimates are constructed excluding a specific region of interest and then projected into the excluded region. Our counterfactual distribution is delivered by estimates from an optimal stopping problem and not from an assumption of smooth behavior. As in prior exercises, counterfactual and actual distributions are compared and a bootstrap procedure is implemented to

provide standard errors and confidence intervals for our measures of missing mass.

Specifically, we use a standard stratified bootstrap (Efron and Tibshirani, 1994). Our bootstrap proceeds in three stages. First, stratifying by year, we independently resample the data set 500 times, constructing each time the one period ahead conditional filing probability bin estimates for the given sample. Second, we implement our maximum likelihood estimation on each sample. This yields 500 estimates of $\hat{\delta}$ and \hat{c} . Third, using these estimates we generate 500 counterfactual distributions for filing behavior. Fourth, we take the difference between the resampled observed filing behavior and counterfactual filing behavior. This yields a distribution of 500 missing mass estimates upon which statistical tests can be implemented.

Developing a counterfactual from a theoretical basis is an important extension relative to prior efforts. First, given that the counterfactual distribution is grounded in theory, rejecting the counterfactual rejects a specific model of behavior. Prior efforts using smoothed polynomial counterfactuals allow one to reject any smooth model, but cannot arbitrate between candidate theories conditional on being smooth. Second, the use of smoothed polynomial predictions requires both that a relevant underlying theory predicts both smooth behavior and continuity through a point of potentially changing incentives (Chetty et al., 2011). In our environment of tax filing, there is no guarantee that behavior be smooth, as filing probabilities may well have a severe point of inflection shortly in advance of the filing deadline. Furthermore, in our environment, the change in incentives is so sharp (i.e., the tax filing centers close), that we observe virtually no data after a given point in time. Our extension demonstrates that missing or excess mass estimators with theoretical foundations not only sharpen the conclusions drawn from rejecting equality of counterfactual and realized distributions, but also expand the scope of application for such methods.

4 Results

We present the results in four steps: First, we present baseline dynamic discrete choice estimates of exponential discounting and missing mass deviations therefrom. We also discuss a number of alternative specifications retaining exponential discounting that also fail to credibly account for

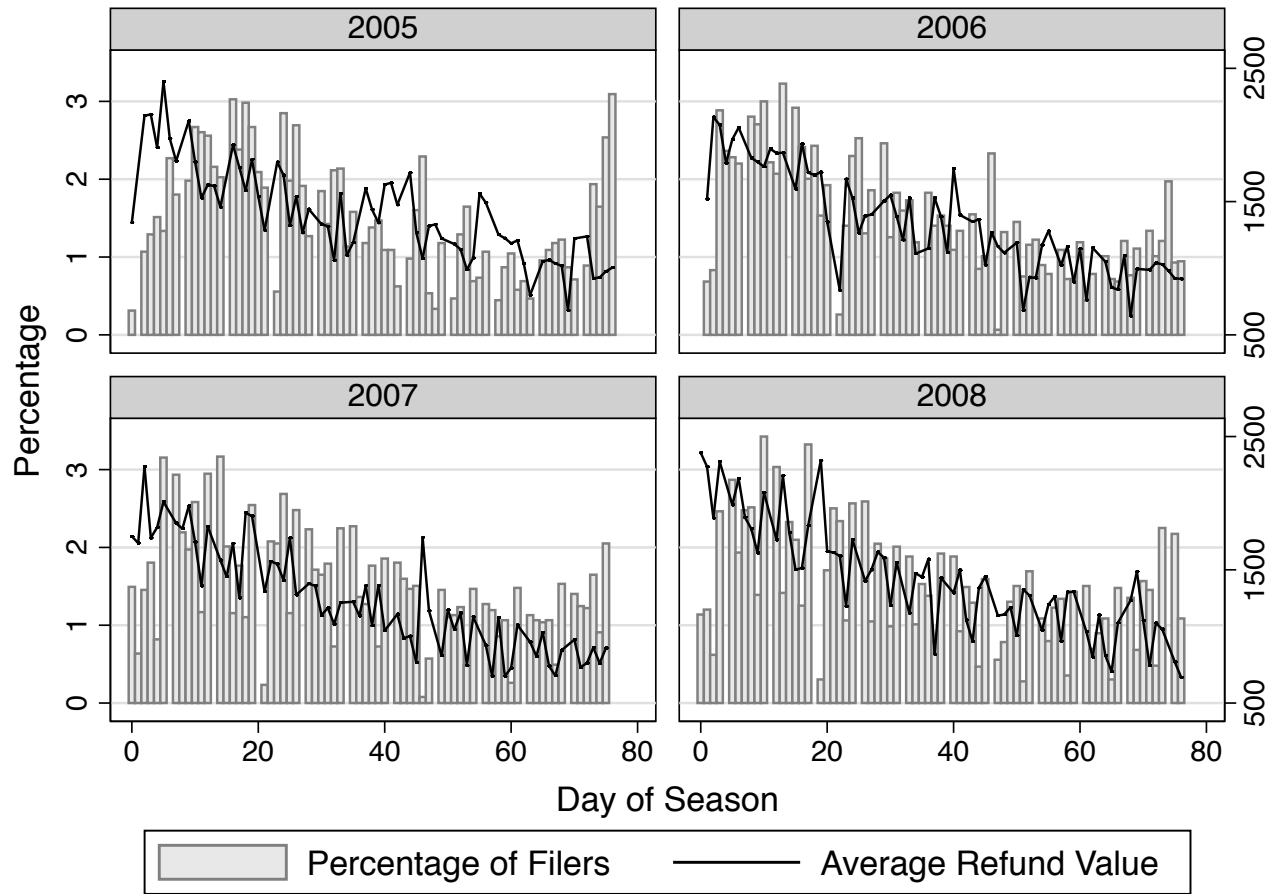
the observed missing mass. Second, we present dynamic discrete choice estimates of present-biased preferences, rationalizing the deviations from exponential discounting in filing behavior at reasonable parameter values. Third, we use the 2008 Stimulus Act and examine the out-of-sample validity of our estimated present-biased model for predicting sensitivities of filing times to changes in filing incentives. Fourth, in a sub-sample of around 1100 subjects we link deviations from exponential discounting in filing behavior to experimental measures of present bias to provide further validation for our behavioral interpretation of the data.

4.1 Estimates of Exponential (δ) Discounting

Figure 1 presents histograms of filing behavior in each year from 2005 to 2008. The figure shows that a large proportion of individuals file early in the tax filing season, with the numbers declining until approximately day 50. From day 50 to the end of the season a pronounced increase in filing is observed. Roughly 9% of filers arrive at VITA sites in the last seven days of operation each year. Also presented in Figure 1 is the average refund value among filers each day. The average value of refunds declines regularly from the beginning of the tax filing season to the end.

Our estimation technique links refund values, filing times, and the timing of refund receipts via a structural model of dynamic discrete choice. A critical component of this procedure is the forecasted future conditional filing probabilities arrived at via rational expectations. As outlined above, we first construct bin estimates for conditional filing probabilities in each year using deciles of refund values. One challenge to creating such values is that VITA sites are closed on holidays and Sundays. We address this by altering our measure of time to reflect only those days where the VITA sites are open each year. A total of 65 days in the tax filing season remain. Note that recognizing a change in the effective timing of choices also requires us to change the intertemporal tradeoffs built in to our estimator.²⁸ For each year, on each day VITA sites are open, in each decile of refund value, we calculate the empirical proportion of individuals who have yet to file who file on that day. A total of

²⁸Recall from section 3.1.1 that we are able to assume that the terminal option is taken in the next period. To account for days that the VITA sites are closed we simply assume that the next period is two periods away resulting in the conditional probability $\frac{p(1_{it}|1_{it},b_i)=1}{1+exp[(\delta^{k+2}-\delta^k)b-(\delta-1)c-\delta\ln(p(1_{i,t+1}|1_{i,t+1},b_i))]}$



Notes: 2005-2008 percentage of filers on each day of tax season (gray bars) and average refund value for filers on each day (black line).

Figure 1: Filing Times and Refund Values

4589 bins are constructed delivering corresponding bin estimates for conditional filing probabilities, $\tilde{p}(1_{i,t+1}|1_{i,t+1}, b_i)$.

Table 2: Aggregate Parameter Estimates 2005 — 2007

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.536 (0.003)	0.592 (0.001)	0.638 (0.000)	0.673 (0.000)	0.718 (0.000)	0.738 (0.000)
\hat{c}	3.341 (0.017)	5 -	10 -	20 -	50 -	75 -
# Observations	1010387	1010387	1010387	1010387	1010387	1010387
Log-Likelihood	-65402.38	-68149.51	-87536.58	-131490.15	-248985.03	-334805.80
$T - 1 : T - 7$ Average						
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.157	0.181	0.197	0.201	0.204	0.205
$T - 1 : T - 7$ Average						
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0053	-0.0041	0.0061	0.0104	0.0114	0.0115

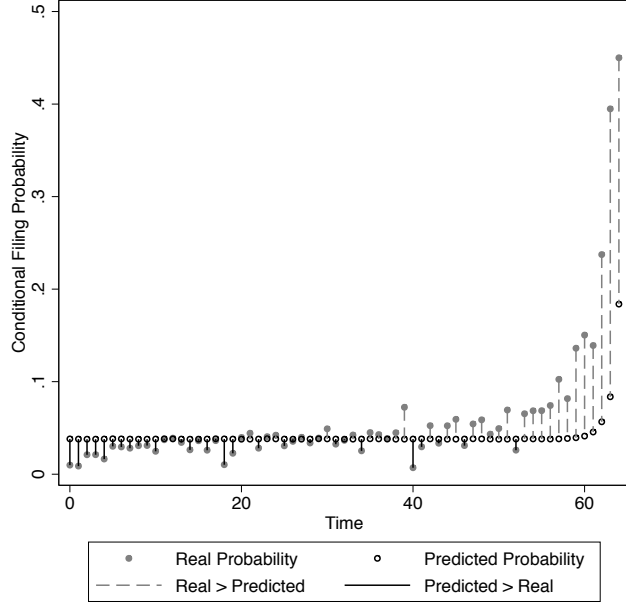
Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline.

Table 2 presents aggregate parameter values based on the data from 2005 to 2007. The data from 2008 and out-of-sample analysis of the 2008 Stimulus Payments are presented in section 4.3. In column (1) we estimate both the discount factor, δ , and filing cost, c , finding an average filing cost of $\hat{c} = 3.341$ and a discount factor of $\hat{\delta} = 0.536$.²⁹ In columns (2) through (6) of Table 2 we impose different levels of cost of filing and vary it from $c = 5$ to $c = 75$. Note that identified likelihoods reduce sharply under restrictions to c , indicating that the likelihood is not apparently flat around the maximum. The estimated discount factor ranges from $\hat{\delta} = 0.59$ to $\hat{\delta} = 0.74$ and increase uniformly as costs increase.

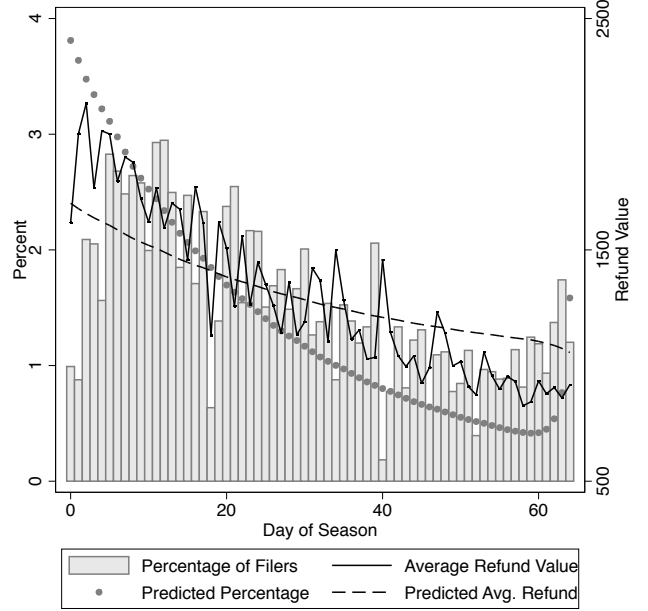
The estimates indicate that even under relatively high parameterizations of costs, estimated

²⁹As discussed in section 3.1.3, our discount factor has two sources of identification. The first comes from the formulation of the problem, yielding differences between the timing of costs and benefits. Without $k > 0$, separate estimation of δ and c would be impossible. In Appendix Table A4, we reconduct the analysis of Table 2 with the assumption of $k = 0$ for all filers. These estimates show the hallmarks of identification problems with flat likelihoods, sensitivity to starting values and, at times, failed convergence. The second comes from the timing impacts of direct deposit. In Appendix Table A5 and A6, we provide separate estimates for individuals with and without direct deposit, showing qualitatively similar, though substantially less precise estimates across the two groups.

Panel A: Conditional Filing Probabilities



Panel B: Filing Times and Refund Values



Notes: Panel A: 2005-2007 predicted and real conditional filing probabilities, $\hat{p}(1_t|1_t)$ and $\tilde{p}(1_t|1_t)$, throughout the tax season with $t = 64$ corresponding to the day before the tax deadline. Panel B: 2005-2007 predicted and real unconditional filing probabilities, $\hat{q}(1_t|1_t)$ and $\tilde{q}(1_t|1_t)$ as gray dots and bars. Predicted and real average refund values in black. All predicted values generated from exponential discounting with $\hat{\delta} = 0.536$ and $\hat{c} = 3.341$ from Table 2, column (1).

Figure 2: Predicted and Actual Filing Behavior

discount factors still remain far from 1. In order to capture empirical regularities of not disproportionately filing early, individuals must substantially discount their filing benefits. Hence, receiving a sizable refund in several week's time can be outweighed by modest filing costs. Estimates of discount factors in the range observed from Table 2 imply discount rates far below empirical rates of interest. When such extreme impatience is required to rationalize empirical behavior in field settings, researchers often appeal to calibrational arguments to reject exponential discounting (Fang and Silverman, 2009; Shapiro, 2005). In contrast, in experimental settings it is not unusual to identify individual discount rates in the hundreds of percents per year (see, e.g., Frederick et al., 2002). Our exercise takes the exponential estimates as a correct benchmark and examines the adherence of intertemporal patterns of filing behavior to theoretical predictions.

Figure 2 presents predicted and actual filing behavior for 2005-2007. In Panel A, we examine

average predicted and actual conditional filing probabilities, $\hat{p}(1_t|1_t)$ and $\tilde{p}(1_t|1_t)$. Predicted and actual conditional filing probabilities correspond closely early in the filing season, but diverge as the tax deadline approaches. On the final two days, $\tilde{p}(1_t|1_t)$ exceeds $\hat{p}(1_t|1_t)$ by around 30 percentage points.³⁰ The exponential counterfactual dramatically underpredicts filing probabilities at the end of the tax season.³¹

Figure 2, Panel B reproduces the daily filing percentages and average refund values from Figure 1³², and also provides corresponding model predictions, $\frac{100}{N} \sum_{i=1}^N \hat{q}(1_t|b_i)$ and \hat{b}_t , respectively. The estimated exponential model over-predicts the percentage of individuals who file early in the season, with substantial under-prediction as the tax deadline approaches. Interestingly, because the model predicts so few people will file during the middle of the tax season, it provides a slight overestimate for the number of filers the day before the deadline. Panel B also highlights that the aggregate estimates predict less sensitivity of filing times to refund values than exists in the data. This result is sensible: given the high degree of impatience, dissimilar refund values have quite similar discounted implications.³³

Table 3 presents estimates of excess mass relative to the exponential benchmark for both conditional and unconditional filing probabilities. The excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, is positive for each of penultimate seven days of the tax season ranging from around 6 to 33 percentage points. On average, from $T - 7$ to $T - 1$, $\tilde{p}(1_t|1_t)$ exceeds $\hat{p}(1_t|1_t)$. Implementing the bootstrap procedure discussed in section 3.3, we find the difference between observed and predicted

³⁰It is important to note that the presented counterfactual distribution is an in-sample prediction. Exercises of missing mass generally leave out a region of interest for estimation. As the focus of our project is procrastination, our primary region of interest is the last seven days of the tax-filing season. In Appendix A, we reconduct our estimation removing the last seven days of the tax filing season (Table A7). As one might expect, misprediction at the end of the tax filing season increases substantially when the last seven days are excluded from estimation. In order to provide more conservative estimates for missing mass we use the full data set for estimation.

³¹In Appendix Figure A2, we present an alternate counterfactual, $\hat{\tilde{p}}(1_t|1_t)$, based on the empirical one-period ahead conditional filing probabilities as opposed to backwards induction. Such a counterfactual makes use of the true one-period ahead behavior, rather than the model's prediction and hence delivers a much less smooth counterfactual distribution. Relative to this benchmark, as well, substantial missing mass is observed.

³²The reproduction adjusts to remove Sundays and holidays.

³³In Appendix Figures A3 and A4, we reconstruct Figure 2 separately for individuals who receive their refund by paper check versus direct deposit. This figure demonstrates that the 60% of individuals receiving paper check are predicted to have virtually constant refund values throughout the tax season. For such a high degree of impatience almost all values of refunds are discounted to a common base of zero. The model fit for direct deposit refund recipients is substantially better.

Table 3: Excess Mass Results

Date	Excess Conditional Probability $\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t)$	Excess Unconditional Probability $\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t)$
$T - 1$	0.325*** (0.018)	-0.0040*** (0.0007)
$T - 2$	0.319*** (0.014)	0.0095*** (0.0008)
$T - 3$	0.141*** (0.011)	0.0081*** (0.0007)
$T - 4$	0.119*** (0.008)	0.0047*** (0.006)
$T - 5$	0.125*** (0.007)	0.0075*** (0.0006)
$T - 6$	0.081*** (0.007)	0.0081*** (0.0007)
$T - 7$	0.058*** (0.006)	0.0038*** (0.0006)
$T - 1 : T - 7$ Average	0.157*** (0.004)	0.0053*** (0.0002)

Notes: Estimates of excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline. Bootstrapped standard errors in parentheses from 500 bootstrap samples.

behavior to be highly significant. Stated in unconditional terms, from $T - 7$ to $T - 1$ an average of 0.65% of filers are predicted to arrive each day, while 1.18% actually do. This equates to around 82% more filers than expected by our counterfactual exponential predictions. The data compellingly reject the estimated model of exponential discounting with $\hat{\delta} = 0.536$ and $\hat{c} = 3.341$.

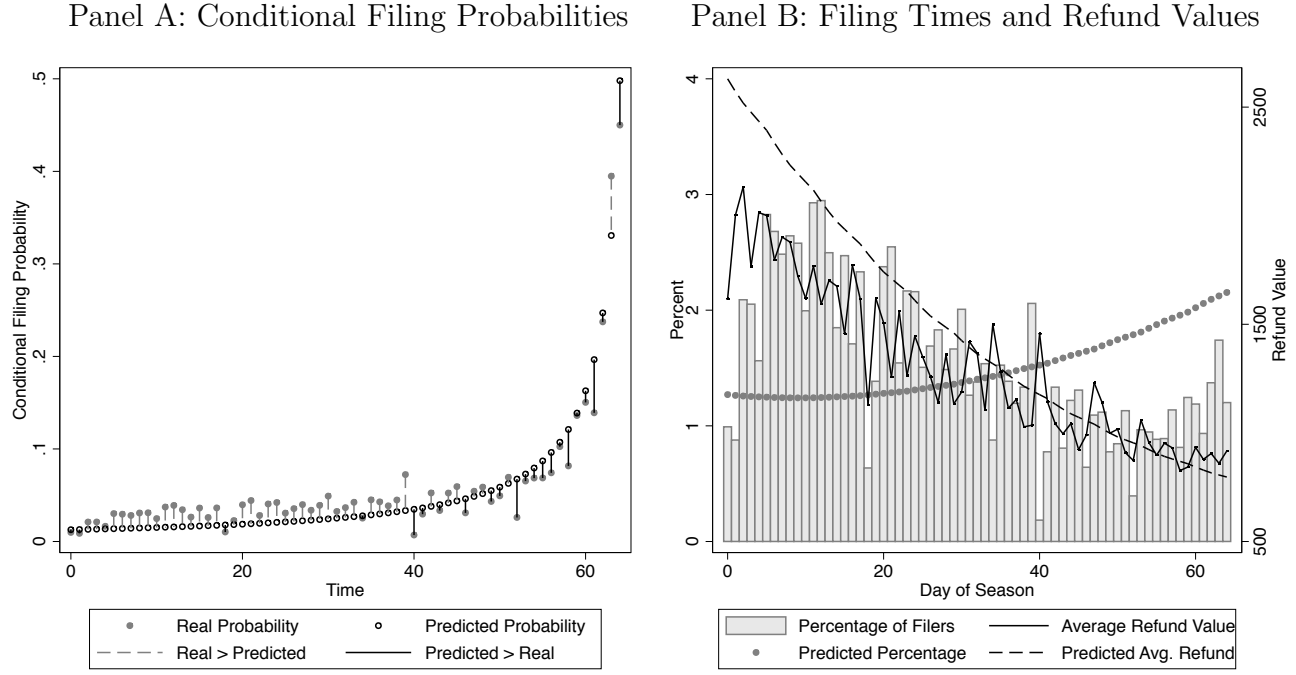
4.1.1 Alternative Exponential Specifications

The results so far demonstrate deviations between the intertemporal patterns of predicted and actual filing behavior. Realized conditional filing probabilities exceed those predicted under exponential discounting by around 30 percentage points in the final days of the tax season. In the last seven days before the tax deadline, this yields an excess mass of filers of around 80%. The data deviate from one particular formulation of an optimal stopping problem developed with assumptions of exponential discounting, rational expectations, homogeneity in costs and discount factors, and iid type-1 extreme value shocks. Failure of any one of these assumptions or others implicit in our development may potentially deliver the observed excess mass of filers at the end of the tax filing season. In the following, we provide a slate of exercises with the objective of examining whether a neoclassical interpretation for the data is compelling, but has been overlooked due to functional form assumptions or misspecifications. Specifically, we investigate extreme costs, extreme shocks, alternate functional forms for utility and heterogeneity in preferences.

Extreme Costs: Table 2 demonstrates that even as costs are fixed at relatively high levels, estimated discount factors remain far outside the range of canonical values. Two natural questions are: if one assumes a specific discount factor close to canonical values, how extreme are estimated costs and how are missing mass estimates altered? Such an exercise links naturally to other exercises in dynamic discrete choice, which fix discount factors to provide credible estimates of other key parameters (see, e.g., Bajari et al., 2007; Kennan and Walker, 2011; Aguirregabiria and Mira, 2007).

In Table 4, column (1) we fix $\delta = 0.999$ corresponding to an annual discount rate of 44%. With this parameter fixed, we estimate $\hat{c} = 3045.2$. Columns (2) and (3) repeat this analysis for $\delta = 0.9999$ and 0.99999 corresponding to around 4% and 1% annual discount rates, respectively. Across specifications, for discount factors close to empirical rates of interest we find cost estimates in the thousands of dollars.

In Figure 3, we reproduce Figure 2, with the counterfactual generated from the highest likelihood specification of Table 4, column (3). Notable from Panel A of Figure 3 are the markedly smaller



Notes: Panel A: 2005-2007 predicted and real conditional filing probabilities, $\hat{p}(1_t|1_t)$ and $\tilde{p}(1_t|1_t)$, throughout the tax season with $t = 64$ corresponding to the day before the tax deadline. Panel B: 2005-2007 predicted and real unconditional filing probabilities, $\hat{q}(1_t|1_t)$ and $\tilde{q}(1_t|1_t)$ as gray dots and bars. Predicted and real average refund values in black. All predicted values generated from exponential discounting with $\delta = 0.99999$ and $\hat{c} = 2199.056$ from Table 4, column (3).

Figure 3: Filing Times and Refund Values (δ (fixed) = 0.99999 and $\hat{c} = 2199.056$)

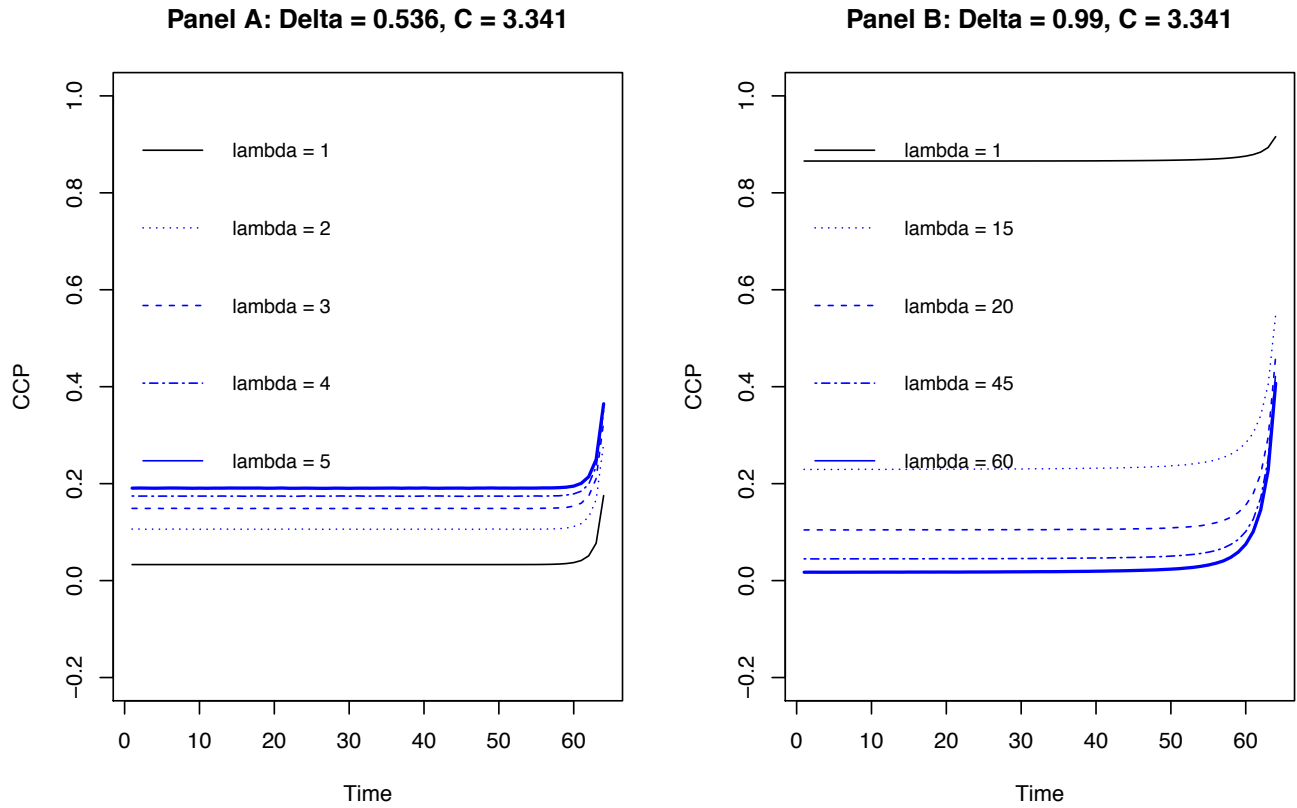
Table 4: Aggregate Parameter Estimates (Fixing Discounting)

	(1)	(2)	(3)
δ (Fixed)	0.999	0.9999	0.99999
\hat{c}	- 3045.216 (5.425)	- 1655.558 (66.519)	- 2199.056 (666.564)
# Observations	1010387	1010387	1010387
Log-Likelihood	-101275.90	-66453.79	-66181.14
$T - 1 : T - 7$ Average			
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.100	-0.006	-0.007
$T - 1 : T - 7$ Average			
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	-0.0130	-0.0404	-0.0086

Notes: Structural estimates of filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007 assuming $\delta \in \{0.999, 0.9999, 0.99999\}$. Assumed level of δ corresponds to annual discount rates between 44% and 1%. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline.

deviations between predicted and actual conditional filing probabilities. One can rationalize intertemporal patterns in filing behavior with canonical levels of discounting. However, the costs required to generate such patterns are extreme, on the order of several thousand dollars. Furthermore, as shown in Panel B, the extreme costs encourage substantial delay, generating increasing proportions of filers through time, and missing the evolution of refund values.

Extreme Shocks: Our model assumes daily i.i.d. shocks associated to both filing and not filing. Intuitively, the difference between these shocks represents the stochastic opportunity cost associated with filing one's taxes on a given day. In every period, an individual evaluates the benefit of filing against the value of waiting for a more favorable pattern of shocks. In such environments the variance of potential shocks is critical. Increasing the scale of shocks has two principle effects. First, the option value of delay is increased as filers have an incentive to wait for future favorable shocks. As the deadline approaches this option value erodes, and one should see increased filing close to the deadline. Second, the incentives to file in any given period are changed. For example, if δ is low and



Notes: 2005-2007 simulated average conditional filing probabilities $p(1_t|1_t)$ under exponential discounting. Simulations of backwards induction behavior under type-1 extreme value shocks with various assumptions for λ , the scale of shocks. Solid black line corresponds to $\lambda = 1$, the assumed value for estimation, and is generated both via simulation and via iterating on $p(1_t|1_t)$ backwards with $p(1_T|1_T) = 1$. Panel A assumes $\delta = 0.536$ and $c = 3.341$, the estimated values from Table 2, column (1). Panel B assumes $\delta = 0.99$ and $c = 3.341$

Figure 4: Shocks and Filing Behavior

individuals are unlikely to file in early periods, increasing the variance of shocks makes it more likely in such periods that an individual will receive a favorable shock constellation and file.³⁴ In contrast, if δ is high and individuals are more likely to file in early periods, increasing the variance of shocks should lead to decreased filing probabilities, as it makes it more likely that individuals receive an unfavorable shock constellation and choose not to file.³⁵

Figure 4 shows simulated conditional filing probabilities as one increases the scale of the type-1

³⁴The negative shocks are less consequential as individuals are already filing with low probability.

³⁵The positive shocks are less consequential as individuals are already filing with high probability.

extreme value shocks from that assumed by our estimation, $\lambda = 1$, to $\lambda = 60$.³⁶ The above-noted effects are demonstrated both for the low level of patience implied by the estimates of Table 2, Column (1) and for $\delta = 0.99$ and $c = 3.34$. When patience is low in Panel A, increased λ can lead to increased filing close to the deadline, but comes with increased filing probabilities early in the tax season. When patience is high in Panel B, increased λ leads to both increased filing close to the deadline and decreased filing early in the tax season. Interestingly, with $\lambda = 60$, one can qualitatively match patterns in intertemporal filing behavior with conditional filing probabilities of around 3% early in the season and close to 40% at the end. However, the scale of shocks required to generate such patterns are extreme. For example, with $\lambda = 60$, an individual at $t = 55$ with a conditional filing probability of 0.03 only files if she observes an opportunity cost \$210 more favorable than the mean. Given a population making an average wage of \$9 per hour, we view this as implausibly extreme.³⁷

Heterogeneity in Preferences and Costs: The data demonstrate increasing filing close to the tax deadline relative to a benchmark of exponential discounting where the heterogeneity across individuals is described only by differences in refund values and direct deposit status. One can imagine other degrees of heterogeneity, the ignorance of which may lead to apparent deviations due to aggregation across types. Though comprehensive exploration of such heterogeneity lies beyond the scope of our data, we can examine whether our measures of excess mass are sensitive to recognizing heterogeneity in preferences or costs along observable characteristics.

³⁶For each of these models we simulate decision making for 500 randomly sampled individuals from our data set. That is, we sample pairs of refund values and direct deposit statuses. We recursively solve the optimization problem, detailed in section 3.1, at various levels of λ – the scale parameter of type-1 extreme value shocks. To this end, we assume a filing probability of 1 in the final period, $t = 65$, and simulate 10000 shocks for each period and possible action. Using the empirical distributions of shocks we calculate the probability of filing in period t as the proportion of realized shocks that induce an individual to file in period t . This proportion is then averaged across the 500 randomly sampled subjects. The location parameter is fixed to $\mu = -\gamma$ throughout, such that the expected value of the shocks along with their variance is changing across specifications. A solid black line is provided corresponding to our benchmark assumptions of $\mu = -\gamma$, $\lambda = 1$. This solid black line is generated both by simulation and by simply iterating backwards the conditional filing probability function, $p(1_{it}|1_{it}, b_i)$ with $p(1_{iT}|1_{iT}, b_i) = 1$, ensuring that our maximum likelihood construction does indeed map to the assumed decisionmaking process.

³⁷It is worth noting that as t get smaller, i.e. further from the deadline, the probability of filing shrinks. This indicates that individuals would only file with opportunity costs more favorable than \$210 better than the mean.

Following the estimation strategy outlined in section 3.1, in Table 5 we allow for either the discount factor or estimated filing costs to depend on the observable demographic characteristics: age, race, gender, and college experience. That is, for each characteristic we allow for the univariate heterogeneity in our likelihood expression, $\delta = \alpha_0 + \alpha_1 X$ or $c = \alpha_0 + \alpha_1 X$, where X is age or an indicator for an individual being black, being male, or having college experience.³⁸ Table 5 reports the excess conditional and unconditional filing probability, averaged over individuals in the final seven days of the tax season after allowing for each type of univariate heterogeneity. With the exception of heterogeneity in discount factors across race, none of these analyses change appreciably the excess mass in filing probability in the final seven days of the tax season.³⁹

Table 5: Heterogeneity in Preferences and Costs

	Heterogeneous Parameter			
	δ		c	
	$T - 1 : T - 7$ Average		$T - 1 : T - 7$ Average	
	$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t)$	$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t)$	$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t)$	$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t)$
Heterogeneity by				
-	0.157	0.0053	0.157	0.0053
Age	0.169	0.0018	0.167	0.0032
Gender	0.151	0.0059	0.151	0.0058
Race	0.056	-0.0022	0.152	0.0062
College Exp	0.195	0.0076	0.151	0.0053

Notes: Table entries correspond to average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, or unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the last seven days prior to the tax deadline allowing for one degree of heterogeneity in either δ or c . Heterogeneity incorporated into likelihood formulation by assuming either $\delta = \alpha_0 + \alpha_1 X$ or $c = \alpha_0 + \alpha_1 X$, where X is age or an indicator for an individual being black, being male, or having college experience. Where heterogeneity in self-reported demographics is analyzed, estimation is performed only on individuals with complete data.

Functional Form for Utility: Our estimation procedure makes two critical assumptions with respect to the nature of utility. First, we posit that filing secures a benefit of size $\delta^k b_i$, effectively assuming that the refund will be consumed, and hence yield utility, entirely in the period it is received. Second, we assume that utility is linear in money. In Tables 6 and 7 we relax these two assumption. In Table 6, we reconduct the analysis of Table 2 assuming that individuals smooth their refund

³⁸Note that his exercise requires the one-period ahead conditional filing probabilities to be recalculated for the source of heterogeneity included in the estimation. We also attempted to examine heterogeneity in observables for c and δ allowing for multivariate heterogeneity, but our maximum likelihood estimations failed to converge on these attempts.

³⁹In Appendix Figure A5, we reconstruct Figure 2 for the most promising of these analyses, heterogeneity in discount factors by race. Though conditional filing probabilities are well-captured by the estimator, the evolution of refund values through time is markedly mis-estimated.

consumption over thirty days.⁴⁰ Assuming such smoothing only marginally alters the estimates. As opposed to our prior estimates of $\hat{\delta} = 0.536$, we estimate $\hat{\delta} = 0.634$ and estimated costs are virtually identical. Even when assuming higher costs, estimated discount factors remain lower than canonical values. Additionally, the excess conditional filing probability at the end of the tax season remains substantial. As opposed to 15.7 percentage points from our prior estimates, the average excess over the penultimate 7 days in Table 6, Column (1) is 14.1 percentage points.

Table 6: Aggregate Parameter Estimates (Allowing Smoothing)

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.634 (0.004)	0.704 (0.001)	0.751 (0.000)	0.782 (0.000)	0.820 (0.000)	0.837 (0.000)
\hat{c}	3.305 (0.022)	5 -	10 -	20 -	50 -	75 -
# Observations	1010387	1010387	1010387	1010387	1010387	1010387
Log-Likelihood	-65390.10	-67053.49	-78504.36	-105805.96	-178727.20	-230049.50
$T - 1 : T - 7$ Average						
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.141	0.156	0.174	0.185	0.195	0.197
$T - 1 : T - 7$ Average						
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0042	-0.0124	-0.0035	0.0064	0.0092	0.0094

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Likelihood contribution adjusted to reflect smoothing of payments over 30 days. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline.

In Table 7 we assume a power functional form for utility of money, $u(b) = b^\alpha$ and provide estimates corresponding to Table 2, column (1) for $\alpha \in \{0.6, 0.7, 0.8, 0.9\}$.⁴¹ Even assuming substantial curvature for utility, estimated discount factors remain far from 1. Additionally, for the highest like-

⁴⁰This changes the estimated choice probability to

$$p(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp \left[(\delta^{k+31} - \delta^k) \frac{b_i}{30} - (\delta - 1)c - \delta \ln(p(1_{i,t+1}|1_{i,t+1}, b_i)) \right]}.$$

Filing in t relative to $t + 1$ ensures $\frac{b}{30}$ more in period $t + k$ and $\frac{b}{30}$ less in period $t + k + 31$.

⁴¹This changes the estimated choice probability to

$$p(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp \left[(\delta^{k+1} - \delta^k) b_i^\alpha - (\delta - 1)c - \delta \ln(p(1_{i,t+1}|1_{i,t+1}, b_i)) \right]}.$$

The estimates of Table 2 correspond to $\alpha = 1$.

likelihood specification, Column (3), excess mass remains substantial, with an average excess conditional filing probability over the penultimate 7 days of 14.6 percentage points.

Table 7: Aggregate Parameter Estimates (Fixing Curvature)

	(1)	(2)	(3)	(4)
$\hat{\delta}$	0.674 (0.005)	0.641 (0.004)	0.605 (0.003)	0.570 (0.003)
\hat{c}	3.331 (0.026)	3.344 (0.023)	3.345 (0.021)	3.344 (0.019)
α	0.6 -	0.7 -	0.8 -	0.9 -
# Observations	1010387	1010387	1010387	1010387
Log-Likelihood	-65386.87	-65371.36	-65370.26	-65381.41
$T - 1 : T - 7$ Average				
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.132	0.140	0.146	0.152
$T - 1 : T - 7$ Average				
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0036	0.0041	.0046	0.0050

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007 Likelihood contribution adjusted to reflect curvature for utility of money, $u(b) = b^\alpha$. Columns (1) - (4) assuming $\alpha \in \{0.6, 0.7, 0.8, 0.9\}$. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline.

4.2 Estimates of Present-Biased ($\beta - \delta$) Discounting

The previous sections demonstrate a substantial deviation between predicted behavior assuming exponential discounting and actual tax filing behavior. Additionally, examination of costs, shocks, smoothing, curvature, and heterogeneity in preferences while retaining exponential discounting have all proven lacking in some way. In this section, we examine the implications of assuming a behavioral model of choice, specifically present-biased preferences.

For this analysis we assume quasi-hyperbolic $\beta - \delta$ discounting of the form proposed by Laibson (1997); O'Donoghue and Rabin (1999). An individual is assumed to discount between the present and a future period with discount factor $\beta\delta$, but discount between any two future periods with discount factor, δ alone. If $\beta < 1$ the individual is 'present-biased', while if $\beta = 1$, the individual behaves as an

exponential discounter.⁴² The quasi-hyperbolic model elegantly delivers deviations from exponential discounting such as self-control problems, procrastination being one potential manifestation. Because such models feature inconsistencies between long run plans and short run behavior, they require the researcher to provide a formulation of the individual's beliefs about their own predilection to be present-biased in the future. For our analysis we make the analytically tractable, but admittedly extreme, assumption that individuals are naive with respect to their present bias. That is, they believe that in the future they will behave as if $\beta = 1$. This assumption and the simplification it generates for analysis is also noted and justified in DellaVigna et al. (Forthcoming).⁴³

Incorporating present bias into our estimation procedure requires several steps. First, as noted in section 3.1, our exponential formulation assumes rational expectations for the construction of one period ahead conditional filing probability bin estimates. A naive present-biased individual deviates from rational expectations in the sense that he believes his filing behavior will follow the path of an exponential discounter rather than the true path. As such the true, rational expectations filing probability $\tilde{p}(1_{it}|1_{it}, b_i)$ does not reflect this decisionmaker's belief and so cannot be used to facilitate estimation. However, the assumption of naivete proves useful in this environment. For a given δ and c , one can solve for the path of beliefs via backwards induction as

$$p_n(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp[(\delta^{k+1} - \delta^k)b_i - (\delta - 1)c - \delta \ln(p_n(1_{i,t+1}|1_{i,t+1}, b_i))]}.$$

and $p_n(1_{i,T}|1_{i,T}, b_i) = 1$. With $p_n(1_{i,t+1}|1_{i,t+1}, b_i)$ as the forecasted future behavior, we can then estimate β via maximum likelihood under the assumed value of δ and c using similar methods as 3.1.⁴⁴ The likelihood contribution for the critical case of $f_{it} = 1$ becomes

$$p_{\beta\delta}(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp[\beta(\delta^{k+1} - \delta^k)b_i - (\beta\delta - 1)c - \beta\delta \ln(p_n(1_{i,t+1}|1_{i,t+1}, b_i))]}.$$

In effect, the estimator replaces the rational expectations beliefs inherent to our exponential con-

⁴²Additionally, the case of $\beta > 1$ is termed 'future-biased'.

⁴³However, the assumption of full naivete would be inconsistent with the substantial literature on commitment demand noted in footnote 1.

⁴⁴The derivation of this expression is presented in Appendix A.3

struction with naive beliefs, and then estimates present bias using these systematically miscalibrated forecasts.

Table 8 provides results from this analysis. In each column, we first use a fixed level of cost and δ to construct $p_n(1_{i,t+1}|1_{i,t+1}, b_i)$. Then we estimate β under these assumed parameters. Notable from Table 8 is the relatively small degree of estimated present bias. With exponential discounting and these values of δ , costs were estimated on the order of several thousand dollars. In contrast, with reasonable value for cost, present bias of only a few percentage points can effectively deliver the same behavior. Of particular importance are the estimates from column (4), the highest likelihood specification. With $\delta = 0.99999$ and costs of $c = 3$, we estimate $\beta = 0.92$, close to recent empirical estimates for present bias from intertemporal effort choices.⁴⁵

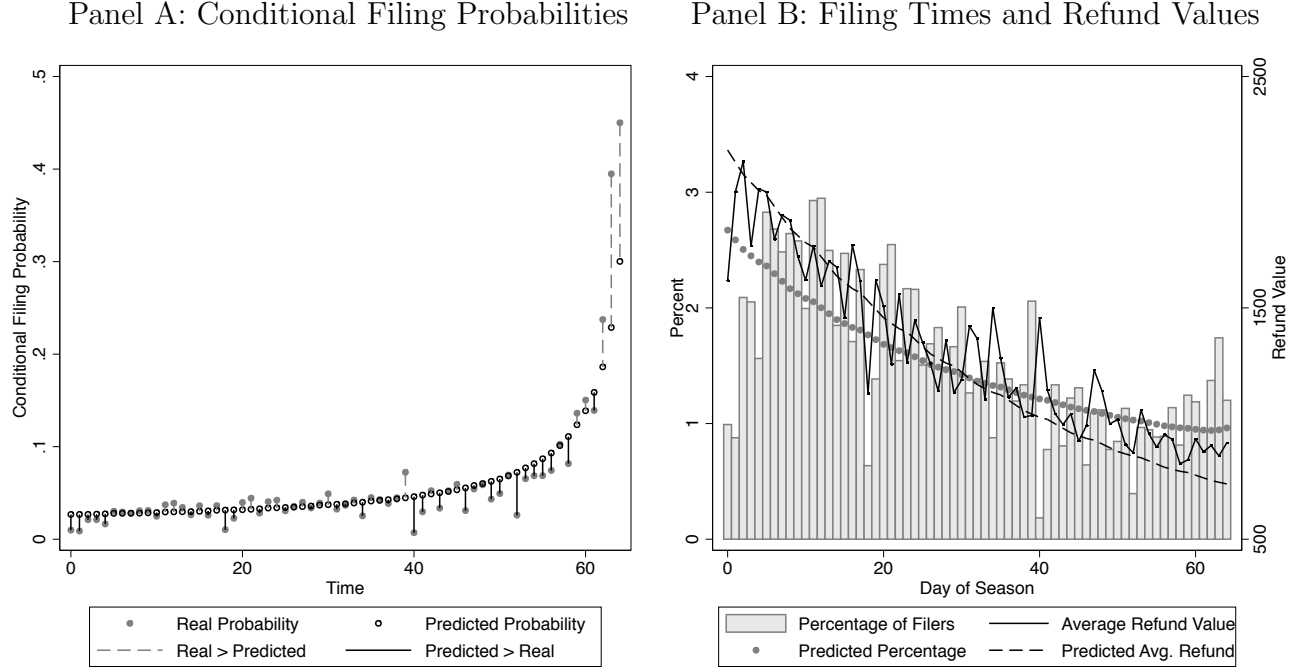
Table 8: Present-Biased (β - δ) Preferences

	(1)	(2)	(3)	(4)	(5)	(6)
β	0.81 (0.001)	0.91 (0.000)	0.98 (0.006)	0.92 (0.011)	0.98 (0.004)	0.99 (0.001)
δ	0.9999	0.9999	0.99999	0.99999	0.99999	0.99999
c	- 10	- 20	- 2	- 3	- 5	- 10
# Observations	1010387	1010387	1010387	1010387	1010387	1010387
Log-Likelihood	-70482.8	-71638.5	-66039.1	-66023.1	-66038.1	-66041.9
$T - 1 : T - 7$ Average $\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.162	0.156	0.032	0.048	0.037	0.032
$T - 1 : T - 7$ Average $\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0007	-0.0007	0.0022	0.0024	0.0014	0.0016

Notes: Structural estimates of quasi-hyperbolic discounting parameter β obtained via Maximum Likelihood Estimation for year 2005-2007. Likelihood contribution adjusted to reflect present bias with naive beliefs, $p_n(1_{i,t+1}|1_{i,t+1}, b_i)$ for a given δ and c . Columns (1) and (2) restrict $\delta = 0.9999$, columns (3) through (6) restrict $\delta = 0.99999$. Costs, c , restricted across columns from 2 to 10. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline.

Allowing for present bias also dramatically alters the extent of excess mass at the end of the tax

⁴⁵Augenblick et al. (2015) estimate $\beta = 0.88$ and Augenblick and Rabin (2016) estimate $\beta = 0.83$ from intertemporal effort choices.



Notes: Panel A: 2005-2007 predicted and real conditional filing probabilities, $\hat{p}(1_t|1_t)$ and $\tilde{p}(1_t|1_t)$, throughout the tax season with $t = 64$ corresponding to the day before the tax deadline. Panel B: 2005-2007 predicted and real unconditional filing probabilities, $\hat{q}(1_t|1_t)$ and $\tilde{q}(1_t|1_t)$ as gray dots and bars. Predicted and real average refund values in black. All predicted values generated from quasi-hyperbolic discounting with $\delta = 0.99999$, $c = 3$ and $\beta = 0.92$ from Table 8, column (4).

Figure 5: Present Bias, Filing Times and Refund Values ($\beta = 0.92$, $\delta = 0.99999$, $c = 3$)

filing season. In Table 8, column (3), the excess conditional filing probability reduces by around 75% compared to our baseline estimates, with $\tilde{p}(1|1_t) - \hat{p}(1|1_t)$ averaging around 5 percentage points over the penultimate 7 days of the tax season. Figure 5 reproduces Figure 2 with these estimates. Quasi-hyperbolic discounting with a relatively modest degree of present bias, $\beta = 0.92$, matches intertemporal patterns in conditional and unconditional filing probabilities as well as the evolution of refund values through time.⁴⁶

Taken together, these analyses show that though there are candidate alternative neoclassical rationalizations for observed conditional filing probabilities, they all require potentially extreme, implausible assumptions. By-and-large these neoclassical alternatives also miss key aspects of in-

⁴⁶In Appendix Figures A6 and A7 we reconstruct Figure 2 separately for individuals who receive their refund by paper check versus direct deposit. This figure demonstrates that the behavior of both paper check and direct deposit refund recipients is well matched by the aggregate estimates, with sensitivity in filing times to refund values predicted for both groups.

tertemporal filing behavior, either the evolution of unconditional filing probabilities or the evolution of refund values through time. In contrast, $\beta - \delta$ discounting with δ close to canonical values, reasonable values of costs, and a relatively mild degree of present bias can rationalize all observed behavior.⁴⁷

4.2.1 The Extent of Procrastination

Present-biased preferences with a moderate degree of present bias provides a credible account of the data from 2005-2007. Estimates in hand, we can deliver a measure of potential procrastination for every tax filer. Consider tax filer i who files on date t with the aggregate parameter levels of β , δ , and c . At date t , two measures are relevant for determining potential procrastination:

$$1 - \Pi_{s=0}^{t-1}(1 - p_n(1_{is}|1_{is}, b_i)),$$

the probability the individual naively believed he would have filed already; and

$$1 - \Pi_{s=0}^{t-1}(1 - \hat{p}_{\beta\delta}(1_{is}|1_{is}, b_i)),$$

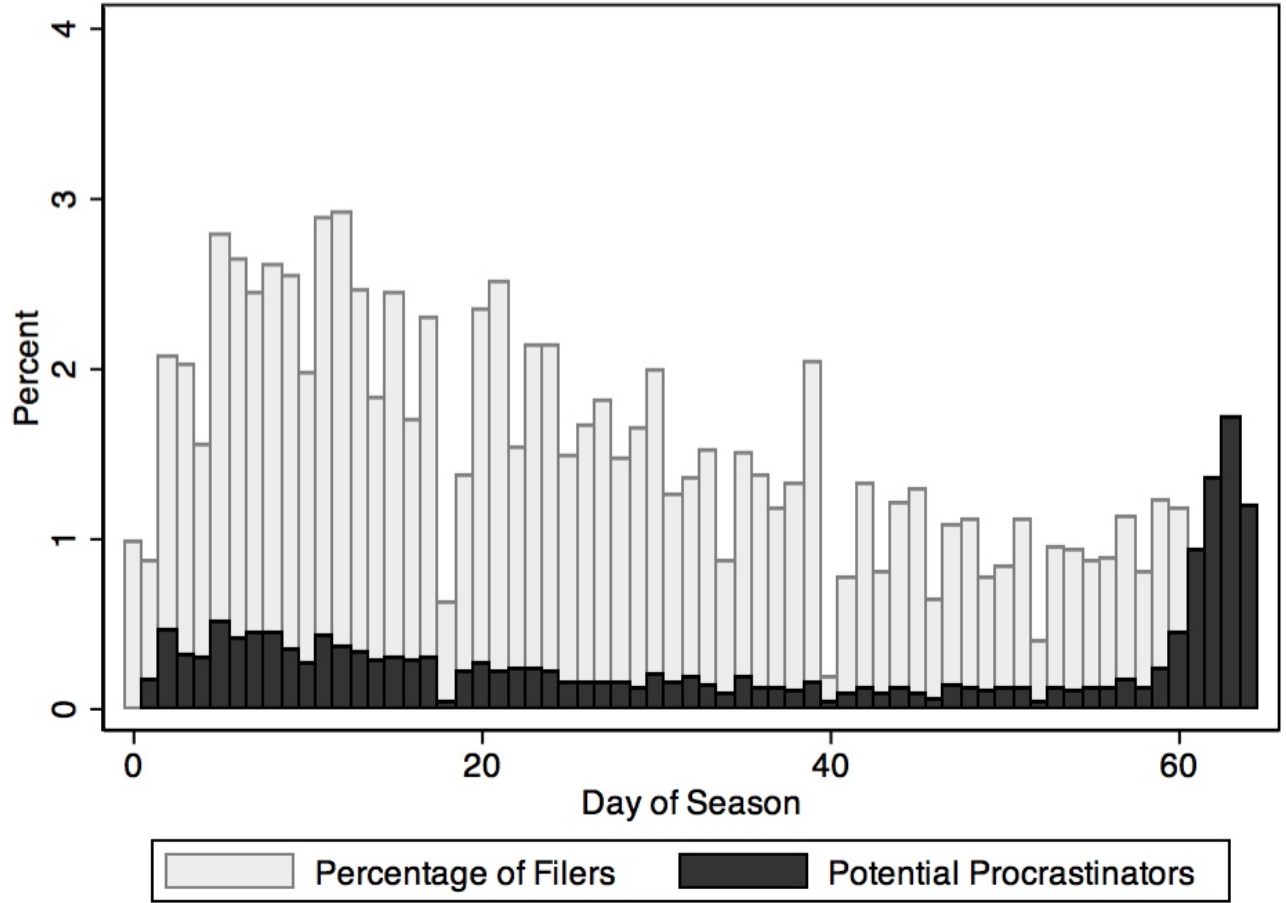
the probability the individual actually would have filed already.⁴⁸ If the individual naively believes it is higher probability that she would have filed in periods 0 to $t - 1$ than it truly was, then she is potentially a procrastinator. Examining such measures on the date of filing is natural as it provides a single, relevant snapshot to evaluate the possibility of procrastination.⁴⁹

Figure 6 reproduces the histograms of filing probabilities from Figure 2, Panel B, highlighting those individuals who could be potential procrastinators. From 2005-2007, twenty-one percent of

⁴⁷Furthermore, these results are reproduced when predicting out-of-sample to filing behavior in 2008. That is, we demonstrate that the out-of-sample fit of intertemporal filing behavior is superior for quasi-hyperbolic preferences relative to the neoclassical model – see appendix figures A8 and A9.

⁴⁸Examination of the formulas for p_n and $p_{\beta\delta}$ will reveal that it is not the case that one of these measures always exceeds the other. Additionally, because refund values and direct deposit status differ across individuals, the difference between these measures will not be identical for all filers.

⁴⁹For example, looking at the difference between these two measures on the last (first) day of the tax filing season for every filer would capture only that many (no) people would have been procrastinators had they filed on the last (first) day.



Notes: 2005-2007 real unconditional filing probabilities, $\tilde{q}(1_t|1_t)$ as light gray bars. Dark gray bars are potential procrastinators on each filing date, t , calculated as proportion of filing individuals for whom $1 - \Pi_{s=0}^{t-1}(1 - p_n(1_{is}|1_{is}, b_i)) > 1 - \Pi_{s=0}^{t-1}(1 - \hat{p}_{\beta\delta}(1_{is}|1_{is}, b_i))$.

Figure 6: Filing Times and Potential Procrastinators

filers are potential procrastinators over the course of the tax season. Notably, as the tax season evolves, the extent of potential procrastination grows. In the penultimate seven days of the filing season roughly seventy-one percent of filers have potentially procrastinated. It must be noted that though the number of potential procrastinators is large, the difference between naive and present-biased probabilities is quite muted. Among filers in the seven days prior to the deadline, the average naive belief on prior filing is calculated to be 95.04%, while the average present-biased probability is 94.85%.

4.3 Response to Changing Incentives: 2008 Stimulus Payments

Rationalizing behavior in-sample with $\beta - \delta$ discounting is important, but does not constitute a stringent test of present-biased preferences. Given that the behavioral model adds a parameter to the standard exponential formulation, one should not be overly surprised by its improved fit. Here, we examine responses to the exogenous changes in filing incentives imposed by the Economic Stimulus Act of 2008 to provide an out-of-sample validation for our behavioral interpretation.

In Figure 7, we provide a difference-in-difference investigation of whether receiving a 2008 Stimulus Payment induced earlier filing. Using the parameters of 2008 Stimulus Act, we calculate (without adjusting for inflation) the value of each individual's potential Stimulus Payment for 2005, 2006, and 2007. We present median filing times (solid lines in both panels) for individuals who would and would not receive Stimulus Payments from 2005 to 2008. In years prior to 2008, those with and without potential Stimulus Payments follow very similar trends with potential recipients filing earlier.⁵⁰ In 2008, the trends diverge. Those without Stimulus Payments in 2008 continue to file later in the tax season, while those with Stimulus Payments file earlier.

Given the apparent response to the 2008 Stimulus Payments, a natural question is how well 2008 filing behavior is predicted both in general and with respect to the sensitivity of filing to Stimulus Payments. For both our estimated benchmark model of exponential discounting, Table 2, column (1), and present bias, Table 8, column (3), we can predict each individual's conditional filing probability

⁵⁰The earlier filing of potential recipients is likely due to the Stimulus Payment's income thresholds and the larger proportional refunds for lower-income individuals in the sample.

in 2008, $\hat{p}(1_{it}|1_{it}, b_i)$ and $\hat{p}_{\beta\delta}(1_{it}|1_{it}, b_i)$, respectively. Similarly, we can construct expected filing days, \hat{t}^* and $\hat{t}_{\beta\delta}^*$.⁵¹ Hence, we can examine both whether out-of-sample our estimates reliably reproduce the patterns in filing behavior in general and the apparent sensitivity to rebate payments.

Along with true filing times, in Figure 7 we present (dotted lines) mean predicted filing times under exponential and $\beta - \delta$ discounting, respectively. These predictions are in-sample for 2005-2007 and out-of-sample for 2008. Panel A demonstrates that the exponential model's predicted filing times are somewhat earlier than true filing times. Importantly, because of the extreme estimated degree of impatience under exponential discounting, the model predicts effectively no responsiveness to the changing incentives generated by the 2008 rebates. In contrast, the estimated model of present bias both matches the difference between potential recipients and non-recipients from 2005-2007 and closely predicts the observed sensitivity to stimulus receipt.

Table 9 shows the results of Figure 7 in more detail. Column (1) provides corresponding regression analysis of the true day of filing, t^* . The results show that receiving a Stimulus Payment in 2008 (coefficient of variable *Interaction*) induced tax filers to arrive 1.92 (s.e. = 0.98) days earlier.⁵² Adding control variables in Column (2) and (3) does not change the results dramatically. So, potential stimulus recipients file earlier in the years 2005 to 2007 and disproportionately so in 2008, the year of the stimulus.

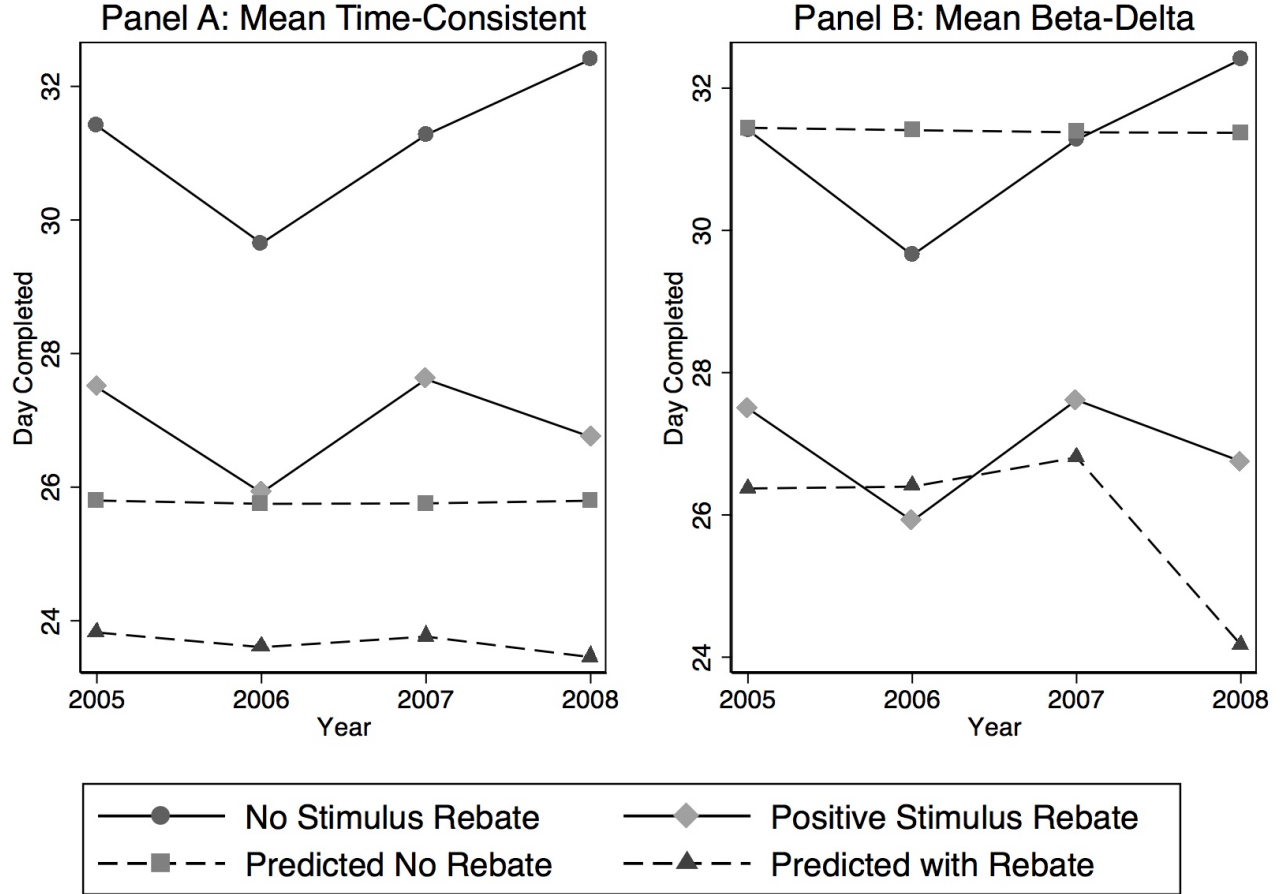
Columns (4)-(9) provide predicted difference-in-difference estimates for the exponential and $\beta - \delta$ predictions – corresponding to the dotted lines in Figure 7. In contrast to the exponential model (in column (4)-(6)), the table demonstrates that $\beta - \delta$ discounting delivers a plausible account both of the average filing times and of the sensitivity of filing times to the 2008 Stimulus Payments. The

⁵¹These values take into account for each individual not only their standard refund, but also their projected 2008 Stimulus Payment. In order to develop this projection, we assume that the Stimulus Payment will be received 14 days after the refund. For example for exponential discounting,

$$\hat{p}(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp \left[(\hat{\delta}^{k+1} - \hat{\delta}^k)b + (\hat{\delta}^{k+14+1} - \hat{\delta}^{k+14})r - (\hat{\delta} - 1)\hat{c} - \hat{\delta} \ln(\hat{p}(1_{i,t+1}|1_{i,t+1}, b_i)) \right]},$$

where r is the Stimulus Payment, with $\hat{p}(1_{iT}|1_{iT}, b_i) = 1$.

⁵²Appendix Table A8 provides a placebo test, turning on the Stimulus Payments in 2007 as opposed to 2008. Null effects of Stimulus Payments are observed, supporting the view that earlier filing dates for payment recipients in 2008 are truly due to the Stimulus Payment and not other factors.



Notes: Mean filing dates, t^* , for potential stimulus recipients (diamonds) and non-recipients (circles) from 2005 to 2008. Panel A: predicted filing date, \hat{t}^* , from exponential discounting for stimulus recipients and non-recipients with $\hat{\delta} = 0.536$ and $\hat{c} = 3.341$, from Table 2, column (1). Predictions are in-sample for 2005-2007 and out-of-sample for 2008, the year of the Stimulus Payments. Panel B: predicted filing date, $\hat{t}_{\beta\delta}^*$, from quasi-hyperbolic discounting with $\delta = 0.99999$, $c = 3$ and $\beta = 0.92$, from Table 8, column (4). Predictions are in-sample for 2005-2007 and out-of-sample for 2008, the year of the Stimulus Payments.

Figure 7: Filing Dates, Stimulus Payments, and Out-of-Sample Predictions

predicted mean response to the stimulus of 2.34 (s.e. = 0.10) days (in column (7)) under $\beta - \delta$ preferences closely matches the true sensitivity of around 2 days.

Table 9: Predicted and Actual Difference-in-Difference Effect of Stimulus Payments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Dep. Var.</i>	t^*			\hat{t}^*			$\hat{t}_{\beta\delta}^*$		
	Observed Filing Day			Exponential Predicted Filing Day			$\beta - \delta$ Predicted Filing Day		
1 ^{Stimulus Rebate > 0}	-3.731*** (0.545)	-1.079* (0.574)	-0.797 (0.593)	-2.044*** (0.042)	0.690*** (0.044)	0.782*** (0.046)	-4.852*** (0.064)	-0.229*** (0.020)	-0.155*** (0.017)
1 ^{Year = 2008}	1.682* (0.944)	1.781* (0.945)	1.744* (0.943)	0.031 (0.022)	0.119 (0.075)	0.114 (0.074)	-0.036 (0.074)	0.056 (0.041)	0.048 (0.034)
Interaction	-1.919* (0.983)	-1.647* (0.982)	-1.766* (0.981)	-0.299*** (0.056)	-0.073 (0.080)	-0.062 (0.079)	-2.346*** (0.103)	-2.136*** (0.044)	-2.154*** (0.037)
Constant	30.722*** (0.520)	31.619*** (0.523)	31.618*** (0.527)	25.766*** (0.015)	26.664*** (0.036)	26.691*** (0.036)	31.408*** (0.029)	32.009*** (0.005)	32.008*** (0.008)
# Observations	22525	22525	22525	22525	22525	22525	22525	22525	22525
Control Set 1	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control Set 2	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Ordinary least squares regression for difference-in-difference effect of Stimulus Payment. Columns (1-3): Dependent variable is actual filing day, t^* . Columns (4-6): Dependent variable is predicted filing day, \hat{t}^* under exponential discounting with $\hat{\delta} = 0.536$ and $\hat{c} = 3.341$, from Table 2, column (1). Columns (7-9): Dependent variable is predicted filing day, $\hat{t}_{\beta\delta}^*$, from quasi-hyperbolic discounting with $\delta = 0.99999$, $c = 3$ and $\beta = 0.92$, from Table 8, column (4). Columns (4-6) and (7-9) predictions are in-sample for 2005-2007 and out-of-sample for 2008, the year of the Stimulus Payments. Standard errors in parentheses.

Control Set 1: Refund, AGI, Direct Deposit Status.

Control Set 2: Number of Dependents, Taxable Income, Earned Income, Social Security Benefits, Filing Status Binaries (2008 stimulus act determinants).

Levels of significance: ***, **, * for 10%, 5%, and 1%, respectively.

4.4 Experimental Present Bias and Tax Filing Behavior

In addition to examining out-of-sample predictive power for $\beta - \delta$ in filing behavior, our environment provides independent means for identifying present-biased preferences. As described in detail in section 2.3, we elicited time preferences experimentally for a subsample of around 1100 individuals in 2007 and 2008.

For each experimental subject we can link their experimental measure of present bias, $Present\ Biased_i$, to their individually fitted pattern of conditional file probabilities, $\hat{p}(1_{it}|1_{it}, b_i)$, and their expected filing date, \hat{t}^* .⁵³ Figure 8, presents real and predicted conditional filing probabilities separately for present-biased and not present-biased subjects. Because our experiment is

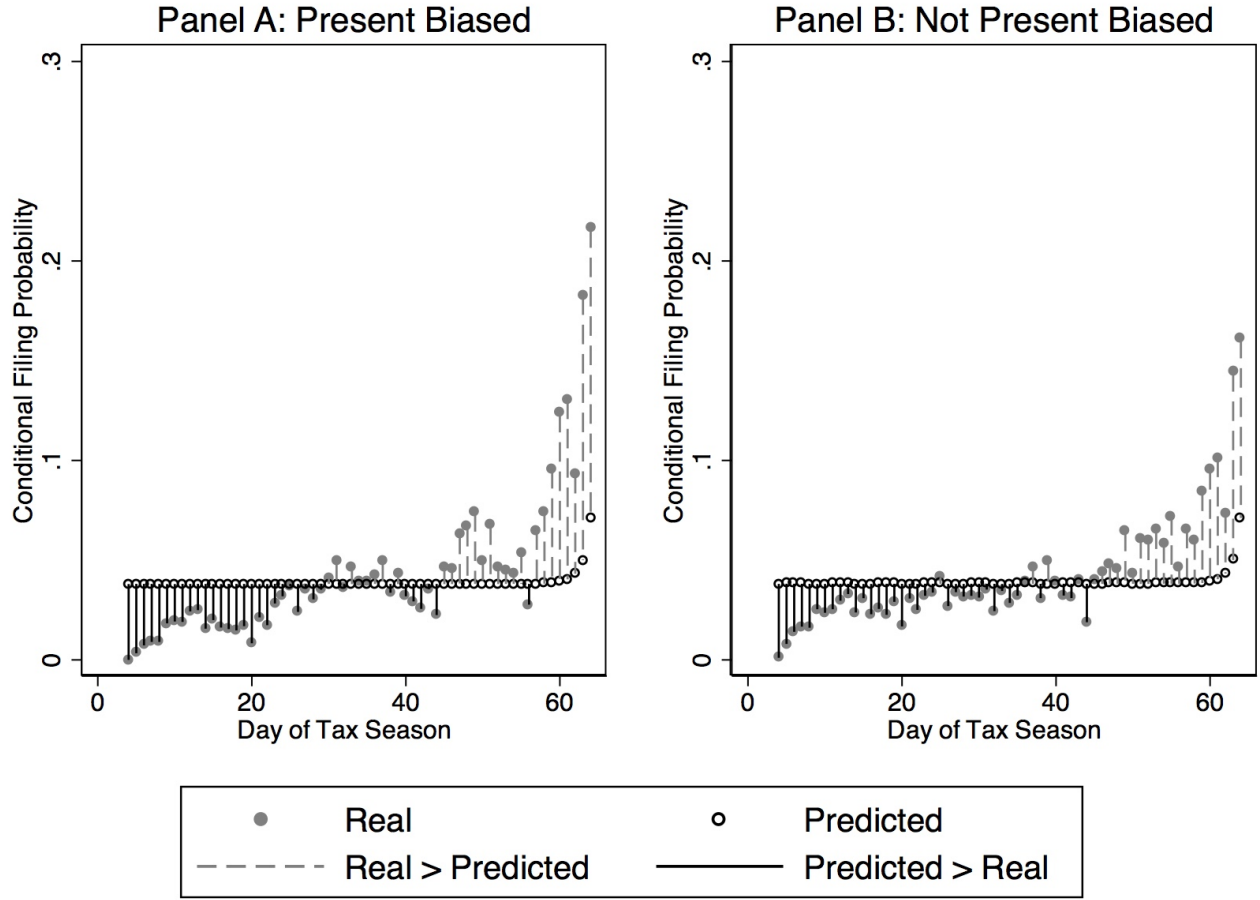
⁵³In order to construct the predicted conditional filing probabilities in-sample for each individual, we re-estimate the baseline exponential model of Table 2, column (1) including the 2008 data (and the Stimulus Payments). The corresponding parameter values are effectively unchanged from those reported in Table 2, column (1) with $\hat{\delta} = 0.527$ and $\hat{c} = 3.295$. From these estimates we construct the counterfactual $\hat{p}(1_{it}|1_{it}, b_i)$ for each individual via backwards induction.

conducted at only one VITA site, which was not open every day of the tax season, a number of days have no individuals filing. Hence, Figure 8 provides 5 day running averages beginning at the tax deadline and moving backwards.⁵⁴

Different patterns of mis-prediction are apparent across present-biased and non present-biased subjects. Though predicted conditional filing probabilities are similar across the two groups, real behavior is markedly different. Present-biased subjects file with higher probability close to the filing deadline and provide greater deviations between predicted and actual behavior than their non present-biased counterparts.

Table 10 provides corresponding analysis. In column (1), we regress predicted conditional filing probabilities, $\hat{p}_t(1_{it}|1_{it}, b_i)$, on the day of filing, t , an indicator for *Present Biased*, and their interaction. Present-biased subjects do not differ in terms of their predicted filing dates at any part of the tax season. In column (2), we present an identical regression with true conditional filing probabilities, $\tilde{p}(1_{it}|1_{it}, b_i)$, as dependent variable. Present-biased subjects indeed file with lower probability at the beginning of the tax season and with greater probability at the end of the tax season. In column (3), we present regressions with the difference, $\tilde{p}(1_{it}|1_{it}, b_i) - \hat{p}(1_{it}|1_{it}, b_i)$, as dependent variable. Present-biased subjects are found to file with lower probability than expected early in the tax filing season and with higher probability than expected late in the tax filing season. Columns (4)-(6) repeat this analysis with predicted and actual filing times, \hat{t}^* and t^* , as dependent variables. Experimentally measured present bias is predictive of filing later in the tax season and filing later than the exponential model prediction. Table 10 demonstrates the plausibility of interpreting our measures of missing mass as evidence of procrastination. Experimental measures of present bias are tightly linked to the exponential model's mis-prediction of filing behavior close to the tax deadline.

⁵⁴The unsmoothed figure is provided in Appendix A Figure A10 and presents qualitatively similar, albeit noisier results.



Notes: 2007-2008 predicted and real conditional filing probabilities, $\hat{p}(1_t|1_t)$ and $\tilde{p}(1_t|1_t)$, throughout the tax season with $t = 64$ corresponding to the day before the tax deadline. Panel A: Present-Biased Subjects ($n = 360$). Panel B: Not Present-Biased Subjects ($n = 754$). All predicted values generated from exponential discounting with $\hat{\delta} = 0.527$ and $\hat{c} = 3.295$. Data smoothed with 5 day running average.

Figure 8: Predicted and Actual Filing Probabilities by Present Bias

Table 10: Present Bias and Deviations from Exponential Prediction

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Conditional Filing Probability			Filing Day		
	Predicted $\hat{p}_t(1_{it} 1_{it}, b_i)$	Observed $\tilde{p}(1_{it} 1_{it}, b_i)$	Difference $\tilde{p}(1_{it} 1_{it}, b_i) - \hat{p}_t(1_{it} 1_{it}, b_i)$	Predicted \hat{t}^*	Observed t^*	Difference $t^* - \hat{t}^*$
Present Biased (=1)	0.0002 (0.0005)	-0.0081*** (0.0023)	-0.0083*** (0.0024)	-0.0121 (0.1687)	2.5545** (1.1365)	2.5666** (1.1156)
Present Biased x Day	0.0000 (0.0000)	0.0003** (0.0001)	0.0003** (0.0001)	-	-	-
Day	0.0000 (0.0000)	0.0011*** (0.0001)	0.0011*** (0.0001)	-	-	-
Constant	0.0372*** (0.0004)	0.0072*** (0.0015)	-0.0300*** (0.0015)	23.5255*** (0.0987)	31.1844*** (0.6722)	7.6588*** (0.6556)
R-Squared	0.002	0.012	0.012	0.000	0.004	0.005
# Filers	1114	1114	1114	1114	1114	1114
# Observations	36736	36736	36736	1114	1114	1114

Notes: Ordinary least squares regression for relationship between experimental measure of present bias, predicted and actual filing behavior. Columns (1) through (3): Dependent variables constructed from predicted and observed conditional filing probabilities, $\hat{p}_t(1_{it}|1_{it}, b_i)$ and $\tilde{p}(1_{it}|1_{it}, b_i)$. Columns (4) through (6): Dependent variables constructed from predicted and observed filing times: \hat{t}^* and t^* . Predicted values constructed under exponential discounting with $\hat{\delta} = 0.527$ and $\hat{c} = 3.295$. Standard errors in parentheses, clustered by individual in columns (1) through (3), robust in columns (4) through (6).

Levels of significance: ***, **, * for 10%, 5%, and 1%, respectively.

5 Conclusion

Procrastination is a critical deviation between long term plans and short term behavior, inconsistent with the neoclassical formulation of exponential discounting. Recognizing the challenges of identifying behavioral models of such deviations in field data, this paper presents a way to potentially identify present-biased procrastination. Combining methods from structural estimation of dynamic discrete choice and inference from missing mass, we show a way in which deviations from a specific model of exponential discounting can be measured. We compare realized tax-filing behavior to counterfactual estimates from an optimal stopping problem developed under the assumption of exponential discounting. In a sample of around 22,000 low-income tax filers, realized and exponentially-predicted distributions of filing probabilities differ dramatically as the tax deadline approaches. The existence and location of the missing mass in tax filing behavior is consistent with quasi-hyperbolic discounting with a relatively small degree of present bias. This interpretation of present bias is bolstered by out-of-sample prediction for the sensitivity of filing times to the 2008 stimulus payments,

and incentivized experimental measures of time preferences.

The results presented here rely on linkages across a diverse set of prior research and may, similarly, have implications across a range of fields. First, the paper shows that using structural estimation to develop counterfactual distributions for behavior may valuably expand the scope of missing mass exercises and sharpen corresponding tests. When using a structural benchmark, one need not rely (as is tradition) on a smooth counterfactual distribution through a point of potentially changing incentives to identify missing mass. Further, one knows precisely the model rejected when realized deviations are observed. Though these points are general, we believe that specific behavioral applications in intertemporal choice could be readily implemented. Stopping problems of the form examined here such as submitting applications, changing retirement plans or credit cards, and mortgage refinance abound, and corresponding behaviors are often anecdotally linked to present-biased preferences. A valuable line of research could emerge from precise structural investigation of whether and the extent to which behavior deviates from exponential benchmarks in these settings. While we show that our missing mass is compellingly rationalized by a form of quasi-hyperbolic discounting, many alternative models exist. Future work in this vein should both investigate other models of time preferences and relax our critical assumption of naïveté.

Second, the paper provides both a rationalization for the observed deviations from exponential discounting and a corresponding out-of-sample validation exercise. Given that many candidate theories can rationalize an observed deviation from a given model, such tests should be viewed as a necessary step to exercises of this form. Different candidate theories could have quite different predictions or welfare implications and so knowing the most appropriate one becomes a critical input both for further study and policy discussion. We believe our exercise shows a path forward particularly for exercises that ascribe behavioral motivations to findings of missing mass. When candidate rationalizations include behavioral models with additional free parameters, better in-sample fit should be viewed as relatively weak evidence of model success.

Third, our interpretation of present bias is bolstered in this paper by incentivized experimental measures. A prominent discussion in the behavioral literature has questioned the use of monetary dis-

counting measures, like ours, for the study of time preferences. In principle, the fungibility of money renders useless such choices for informing the researcher about consumption preferences. Predicting individual differences in procrastination in the timing of tax-filing — presumably a consumption preference related to labor-leisure tradeoffs— problematizes such a view. Clearly, future research is needed to fully understand how, when, and why monetary measures of discounting convey valuable information on preferences.

Last, but not least, the paper can identify and quantify procrastination in the field for the low income sample in question. Our results show that roughly seventy-one-five percent of filers in the last week before the deadline are potential procrastinators. Though we cannot extrapolate from this prevalence among low-income filers to the broader population, there may be reasons to be interested in this population specifically. Low income individuals access a number of government services in a similar way to our intertemporal filing problem. Benefits such as food stamps and temporary assistance to needy families must be signed up for initially. Benefits in place, the spending of corresponding receipts is another intertemporal problem. If the level of present-biased procrastination measured in our sample is indicative of behavior in accessing and spending such benefits, policy makers may well be interested in altering the timing of costs and benefits to achieve coverage and smoothing objectives. Though such targeted policy discussions are now equipped with a key observation on the potential extent of procrastination, broader debates about the nature and extent of present bias will require further investigation in more broad populations.

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A Appendix

A.1 Additional Tables and Figures

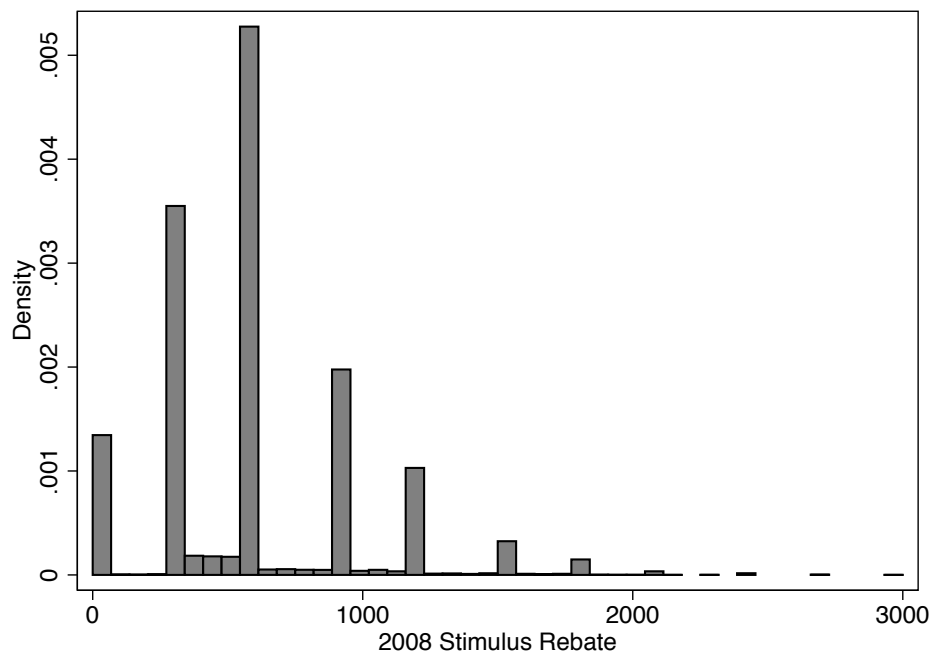


Figure A1: Histogram of 2008 Stimulus Act Rebates

Table A1: Summary statistics

Variable	Roxbury Filers				Full	
	Experimental		Non-Participating			
	Obs	Mean	Obs	Mean	Obs	Mean
Age	1296	38.85 (14.90)	606	40.65 (16.22)	26228	37.80 (15.47)
AGI	1296	17452 (13991)	606	18498 (15179)	26248	16914 (13586)
Refund	1296	1317 (1571)	606	1205 (1482)	26248	1438 (1641)
Dependents	1296	0.505 (0.838)	606	0.418 (0.769)	26248	0.567 (0.90)
1 _{Unemployed}	1296	0.101 (0.302)	606	0.112 (0.316)	26247	0.095 (0.29)
Female	1217	0.644 (0.479)	557	0.636 (0.482)	19881	0.646 (22.03)
Black	1211	0.761 (0.426)	556	0.781 (0.414)	19565	0.562 (0.49)
College	1180	0.138 (0.345)	534	0.133 (0.340)	18971	0.154 (0.36)
Days Until Deadline	1296	38.74 (21.28)	606	46.47 (24.00)	26248	43.07 (22.03)
1 _{Direct Dep}	1296	0.444 (0.497)	606	0.398 (0.490)	26248	0.389 (0.49)

Table A2: Aggregate Parameter Estimates 2007

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.539 (0.004)	0.594 (0.001)	0.639 (0.000)	0.673 (0.000)	0.717 (0.000)	0.738 (0.000)
\hat{c}	3.279 (0.028)	5 -	10 -	20 -	50 -	75 -
# Observations	404191	404191	404191	404191	404191	404191
Log-Likelihood	-26323.63	-27521.71	-35519.37	-53546.81	-101781.32	-137074.84
$T - 1 : T - 7$ Average $\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.172	0.198	0.214	0.219	0.221	0.222
$T - 1 : T - 7$ Average $\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0056	-0.0046	0.0057	0.0102	0.0111	0.0112

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline. This table is a reproduction of 2 but only uses 2007 data.

Table A3: Aggregate Parameter Estimates 2005 — 2007, $\mu = 0$

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.534 (0.003)	0.600 (0.001)	0.642 (0.000)	0.675 (0.000)	0.719 (0.000)	0.739 (0.000)
\hat{c}	2.829 (0.016)	5 -	10 -	20 -	50 -	75 -
# Observations	1010387	1010387	1010387	1010387	1010387	1010387
Log-Likelihood	-65463.96	-70339.45	-91413.34	-135908.46	-253558.83	-339385.71
$T - 1 : T - 7$ Average						
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.131	0.173	0.191	0.196	0.201	0.202
$T - 1 : T - 7$ Average						
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0096	-0.0043	0.0061	0.0104	0.0113	0.0116

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline. This table is a reproduction of 2 with location parameter $\mu = 0$ (as opposed to $\mu = -\gamma$)

Table A4: Aggregate Parameter Estimates 2005 — 2007, $k = 0$

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.99999 (0.000004)	0.9999999 (0.000)	0.999999 (0.000)	0.999999 (0.000)	0.999999 (0.000)	0.999999 (0.000)
\hat{c}	2698.49 (1397.35)	5 -	10 -	20 -	50 -	75 -
# Observations	1010387	1010387	1010387	1010387	1010387	1010387
Log-Likelihood	-66180.702	-66182.362	-66182.361	-66182.359	-66182.352	-66182.346
$T - 1 : T - 7$ Average						
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	-0.015	-0.018	-0.0189	-0.0189	-0.0190	-0.0190
$T - 1 : T - 7$ Average						
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	-0.0078	-0.0025	-0.0025	-0.0024	-0.0025	-0.0025

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline. This table is a reproduction of 2 with no delay in rebate arrival ($k = 0$).

Table A5: Aggregate Parameter Estimates 2005 — 2007, Paper Check

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.631 (0.007)	0.701 (0.001)	0.743 (0.000)	0.770 (0.000)	0.803 (0.000)	0.818 (0.000)
\hat{c}	3.459 (0.030)	5 -	10 -	20 -	50 -	75 -
# Observations	623282	623282	623282	623282	623282	623282
Log-Likelihood	-40689.023	-41397.661	-47599.246	-63972.131	-110885.69	-145574.88
$T - 1 : T - 7$ Average						
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.154	0.166	0.187	0.196	0.205	0.207
$T - 1 : T - 7$ Average						
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0044	-0.0095	-0.0015	0.0093	0.0131	.0135

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline. This table is a reproduction of 2 with only those who receive their rebates via paper checks.

Table A6: Aggregate Parameter Estimates 2005 — 2007, Direct Deposit

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.515 (0.005)	0.588 (0.001)	0.634 (0.000)	0.669 (0.000)	0.714 (0.000)	0.734 (0.000)
\hat{c}	3.16 (0.033)	5 -	10 -	20 -	50 -	75 -
# Observations	387105	387105	387105	387105	387105	387105
Log-Likelihood	-24652.468	-25507.62	-30975.57	-44183.668	-81480.071	-109392.39
$T - 1 : T - 7$ Average						
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.164	0.176	0.187	0.194	0.202	0.205
$T - 1 : T - 7$ Average						
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0040	-0.0047	-0.0003	0.0045	.0067	0.0071

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline. This table is a reproduction of 2 with only those who receive their rebates via direct deposit.

Table A7: Aggregate Parameter Estimates 2005 — 2007, Exclude Last 7 Days

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$	0.527 (0.003)	0.590 (0.001)	0.638 (0.000)	0.673 (0.000)	0.717 (0.000)	0.738 (0.000)
\hat{c}	3.410 (0.018)	5 -	10 -	20 -	50 -	75 -
# Observations	916368	916368	916368	916368	916368	916368
Log-Likelihood	-62214.02	-64532.95	-82175.01	-122525.93	-230511.93	-309418.03
$T - 1 : T - 7$ Average						
$\tilde{p}(1_t 1_t) - \hat{p}(1_t 1_t) :$	0.131	0.173	0.191	0.196	0.201	0.202
$T - 1 : T - 7$ Average						
$\tilde{q}(1_t 1_t) - \hat{q}(1_t 1_t) :$	0.0096	-0.0043	0.0061	0.0104	0.0113	0.0116

Notes: Structural estimates of exponential discounting, $\hat{\delta}$, and filing costs, \hat{c} , obtained via Maximum Likelihood Estimation for years 2005-2007. Columns (2) - (6) restrict costs to be between 5 and 75. Standard errors in parentheses. Also reported is the average excess conditional filing probability, $\tilde{p}(1_t|1_t) - \hat{p}(1_t|1_t)$, and the average excess unconditional filing probability, $\tilde{q}(1_t|1_t) - \hat{q}(1_t|1_t)$, over the seven days prior to the tax deadline. This table is a reproduction of 2 while dropping the last 7 days prior to the deadline.

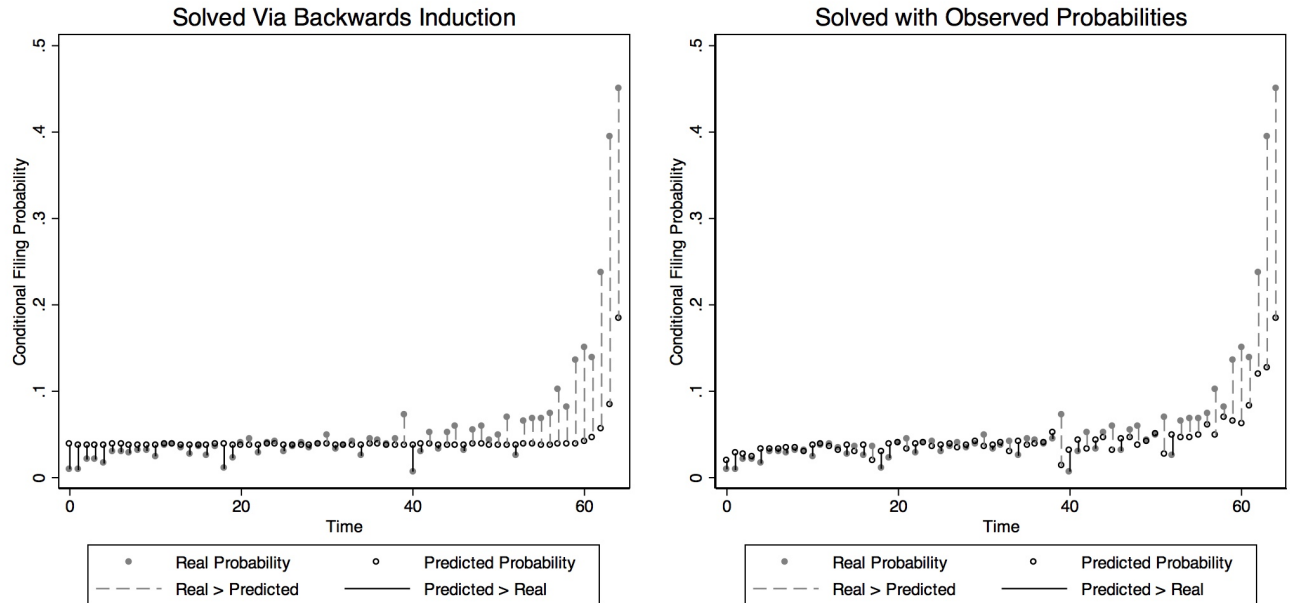


Figure A2: Predicted Filing Times Using 1-Period-Ahead Observed Probabilities

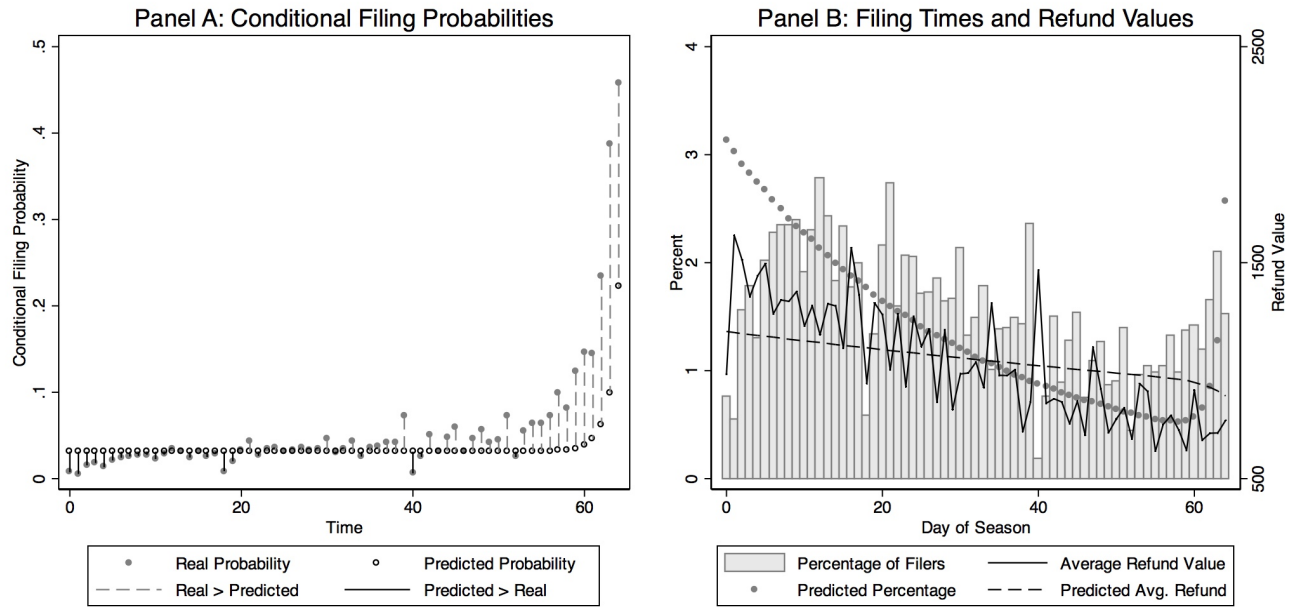


Figure A3: Filing Times and Refund Values (Paper Check Only)

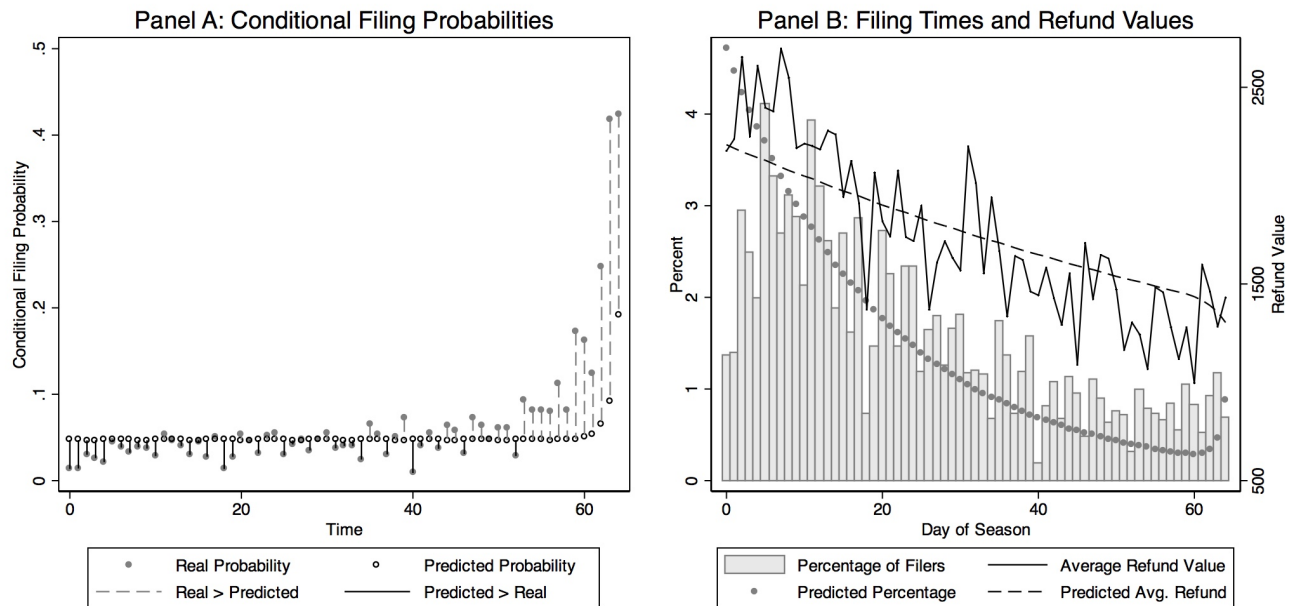


Figure A4: Filing Times and Refund Values (Direct Deposit Only)

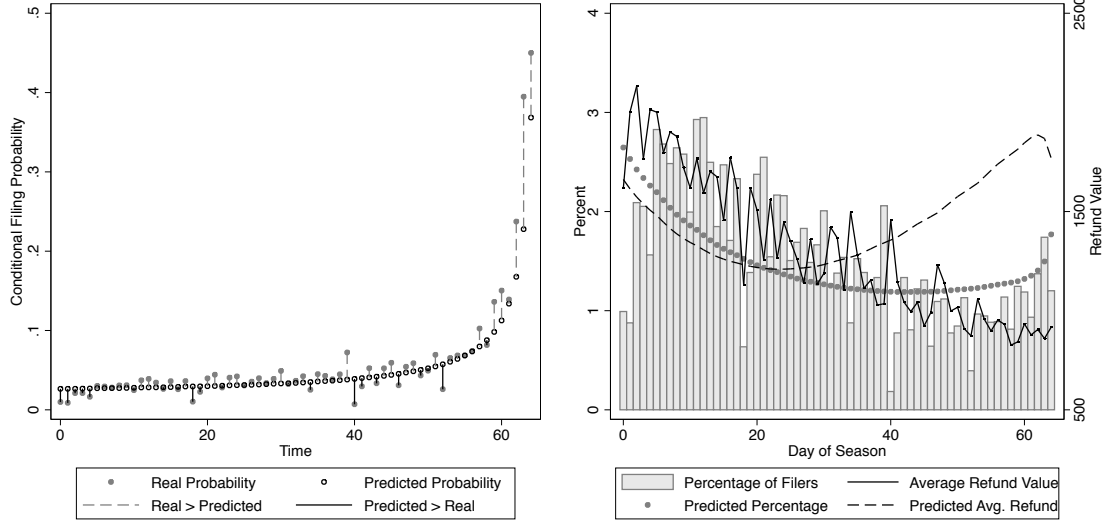


Figure A5: Filing Times and Refund Values (δ Heterogeneous by Race)

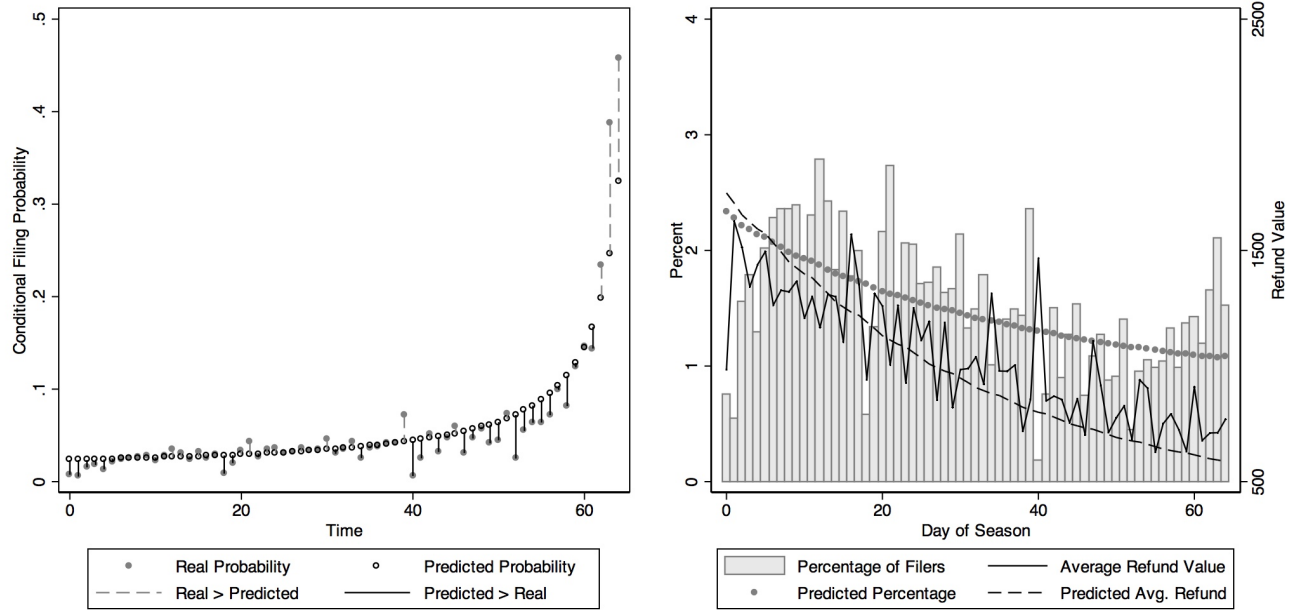


Figure A6: Filing Times and Refund Values (Present Biased, Paper Check Only)

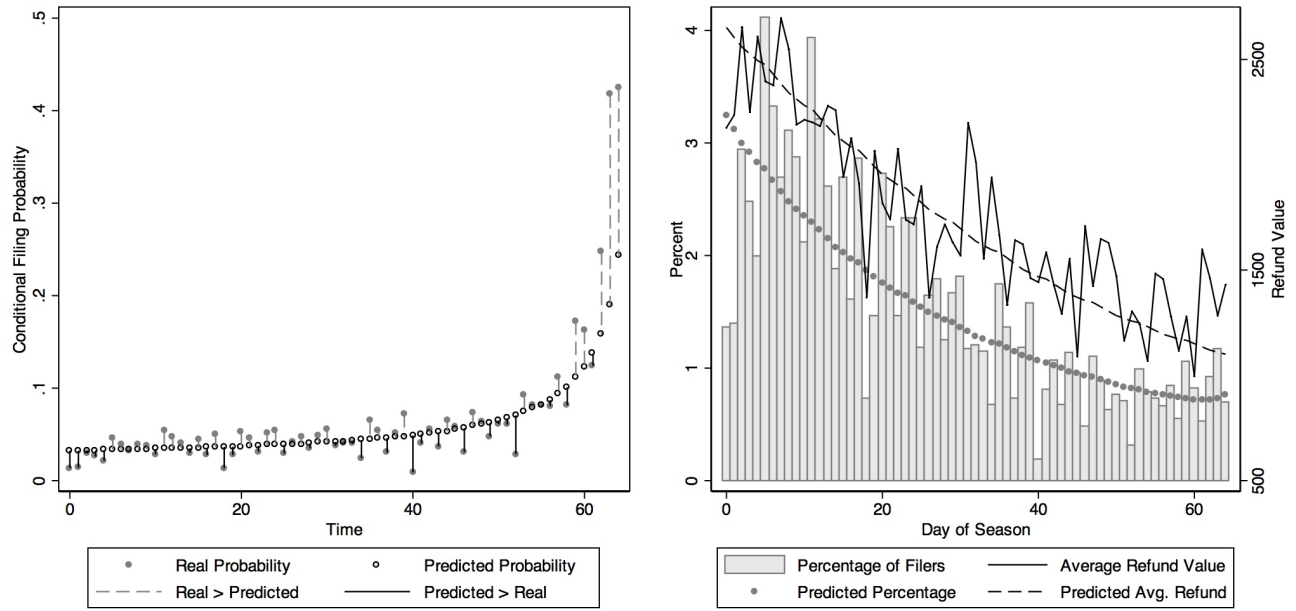


Figure A7: Filing Times and Refund Values (Present Biased, Direct Deposit Only)

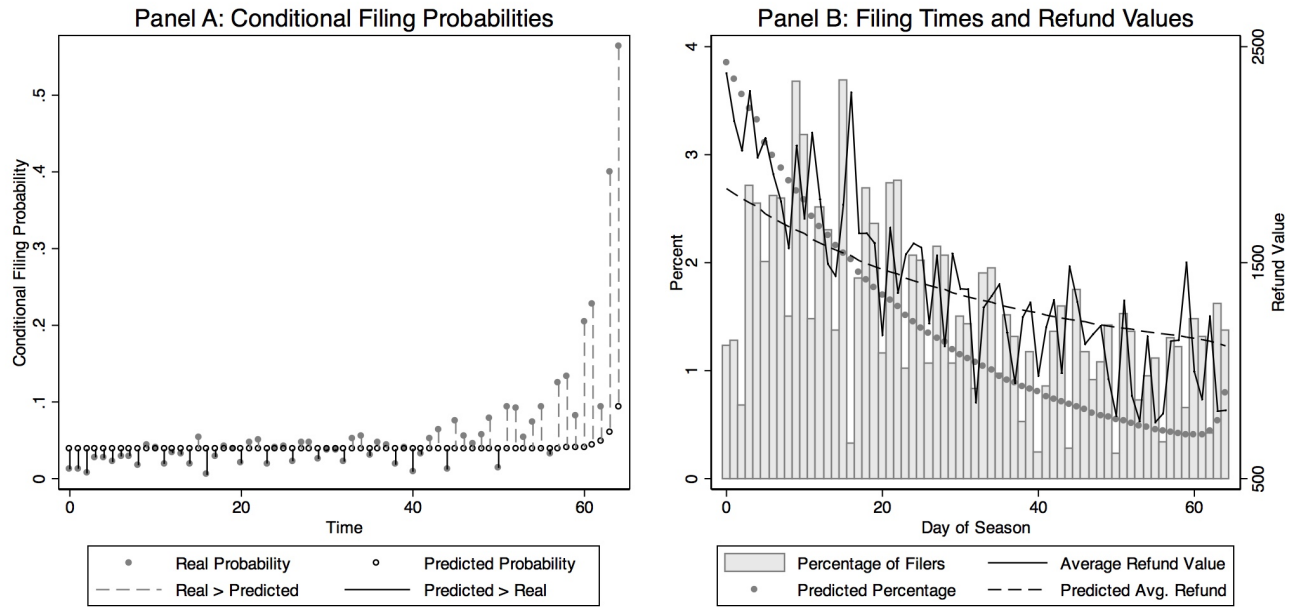


Figure A8: Filing Times and Refund Values 2008 (Time Consistent)

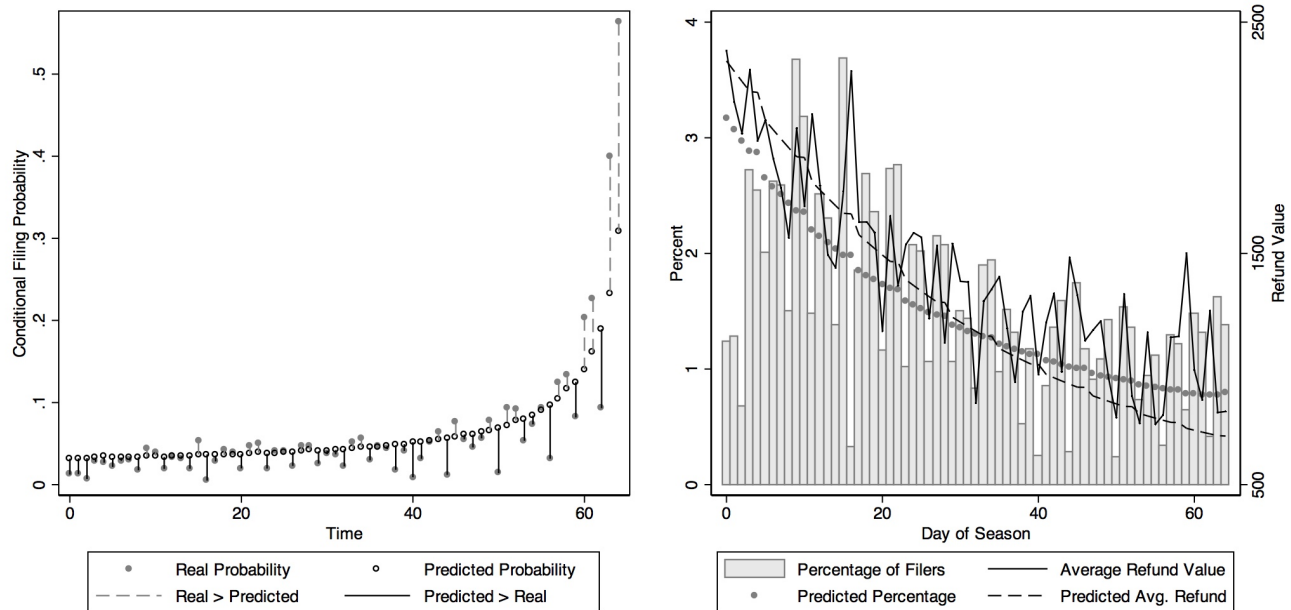


Figure A9: Filing Times and Refund Values 2008 (Present Biased)

Table A8: Difference-in-Difference Effect of Stimulus Payments (Placebo)

<i>Dep. Var.</i>	Linear Regression		Quantile Regression	
	(1)	(2)	(3)	(4)
Day Completed	Day Completed	Day Completed	Day Completed	Day Completed
$1_{\text{Stimulus Rebate} > 0}$	-1.0031 (0.7062)	-0.6341 (0.7276)	-0.9228 (1.1911)	-0.6009 (1.1570)
$1_{\text{Year} = 2007}$	1.0079 (1.0067)	0.9760 (1.0075)	2.2275 (1.8180)	2.2980 (1.7438)
Interaction	-0.3734 (1.0505)	-0.5533 (1.0512)	-0.2586 (1.8638)	-0.4975 (1.7892)
Constant	31.2434*** (0.6427)	31.2478*** (0.6463)	28.1119*** (1.1218)	28.0560*** (1.0675)
Stimulus Determinants	No	Yes	No	Yes
# Observations	15972	15972	15972	15972

Notes: This table demonstrates the relationship between when one filed (Day Completed) and whether one received a 2008 stimulus rebate. This is placebo test of the interaction between $1_{\text{Year} = 2007}$ and $1_{\text{Stimulus Rebate} > 0}$. Standard errors are cluster by individual.

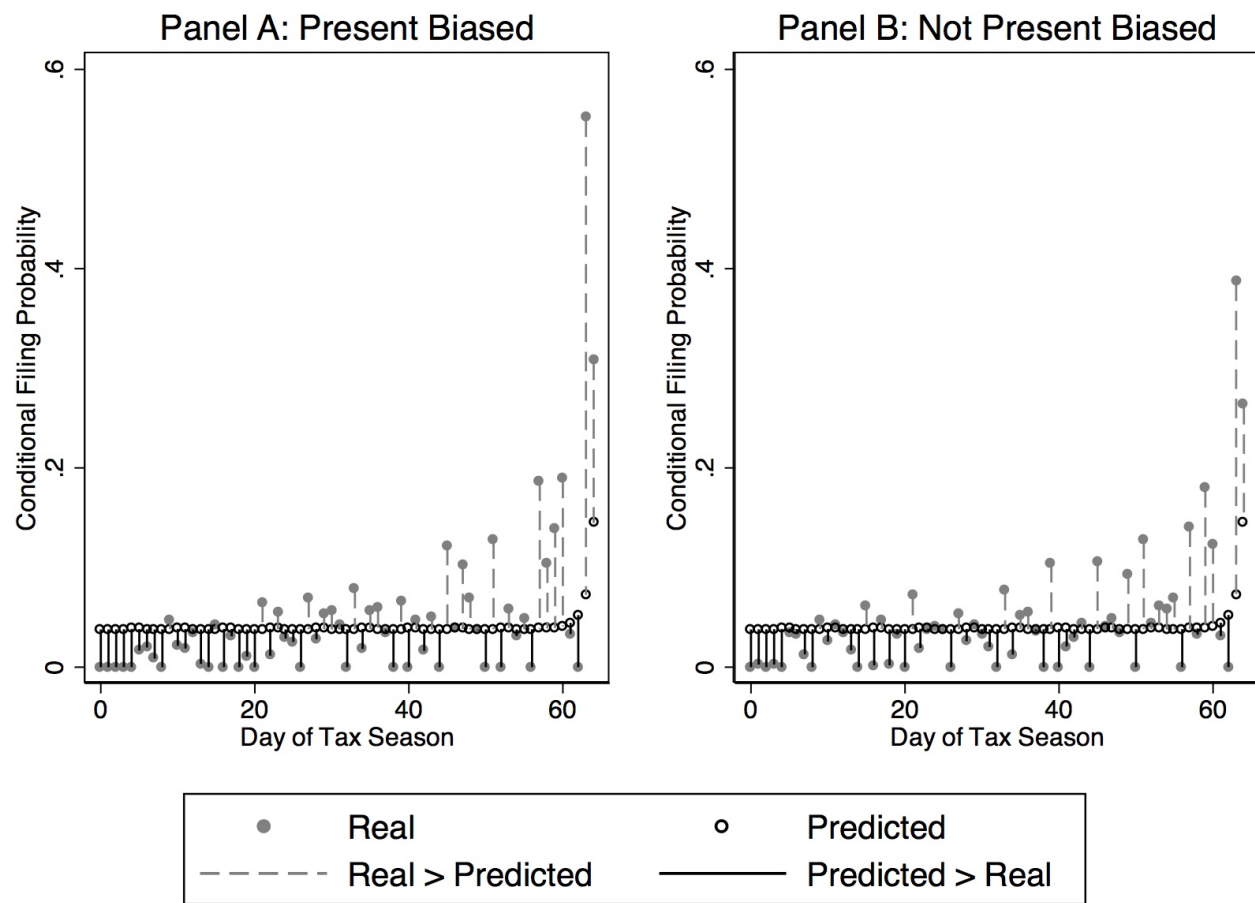


Figure A10: Predicted and Actual Filing Behavior by Present Bias (Un-smoothed)

A.2 Refund Arrival Delay and Identification

We first address the importance in identification of $k > 0$. Recall that the likelihood expression of observation t for individual i is:

$$p(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp[\delta^k(\delta - 1)b - (\delta - 1)c - \delta \ln(p(1_{i,t+1}|1_{i,t+1}, b_i))]}.$$

If we let $k = 0$ then the likelihood expression becomes:

$$p(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp[(\delta - 1)b - (\delta - 1)c - \delta \ln(p(1_{i,t+1}|1_{i,t+1}, b_i))]}.$$

Note that when $k = 0$, b and c must be weighted equally in the likelihood expression. This presents a problem in identification. Since $(\delta - 1)b - (\delta - 1)c = (\delta - 1)(b - c)$, the level sets of $p(1_{it}|1_{it}, b_i)$ in the (δ, c) plane coincide across time periods when solving $p(1_{it}|1_{it}, b_i)$ recursively. This is illustrated in Figure A11. Figure A11 displays the level sets of $p(1_{it}|1_{it}, b_i)$ – assuming $\delta = 0.535$, $c = 10$, refund = 50 – over time periods $t = 61, 62, 63$, and 64 in the (δ, c) plane. We observe that the levels sets separate over different time periods when $k = 14$, but find no such separation when $k = 0$.

In our identification, we take $p(1_{it}|1_{it}, b_i)$, $p(1_{i,t+1}|1_{i,t+1}, b_i)$, and b as given, and we estimate δ and c via maximum likelihood. We know by observation that $p(1_{it}|1_{it}, b_i) \in (0, 1]$, $\ln(p(1_{i,t+1}|1_{i,t+1}, b_i)) \in [-6.59, 0]$ and that the mean refund is \$1419. As such, for any $0 < \delta < 1$ and reasonable cost parameter c , $\exp[(\delta - 1)b - (\delta - 1)c - \delta \ln(p(1_{i,t+1}|1_{i,t+1}, b_i))] \approx 0 \implies p(1_{it}|1_{it}, b_i) = \frac{1}{1 + \exp[(\delta - 1)b - (\delta - 1)c - \delta \ln(p(1_{i,t+1}|1_{i,t+1}, b_i))]} \approx 1$. That is, for reasonable values of c , $p(1_{it}|1_{it}, b_i)$ is computationally 1. However, if $k > 0$ the relative size of the refund does not necessitate that $p(1_{it}|1_{it}, b_i) = 1$. This point is illustrated in Figure A12. Figure A12 recreates figure A11 but assumes refund = 1400. We observe that the levels sets separate over different time periods when $k = 14$. However, when $k = 0$, $p(1_{it}|1_{it}, b_i) = 1$ for all c when fixing any δ . As such, the level sets not only coincide over all time periods, but coincide over (δ, c) within a time period. Unsurprisingly, when running our estimator under the assumption $k = 0$ we find a flat likelihood over all values of c – see Figure A4. In Figure A13 we see further separation of level curves between time periods when increasing k to 21.

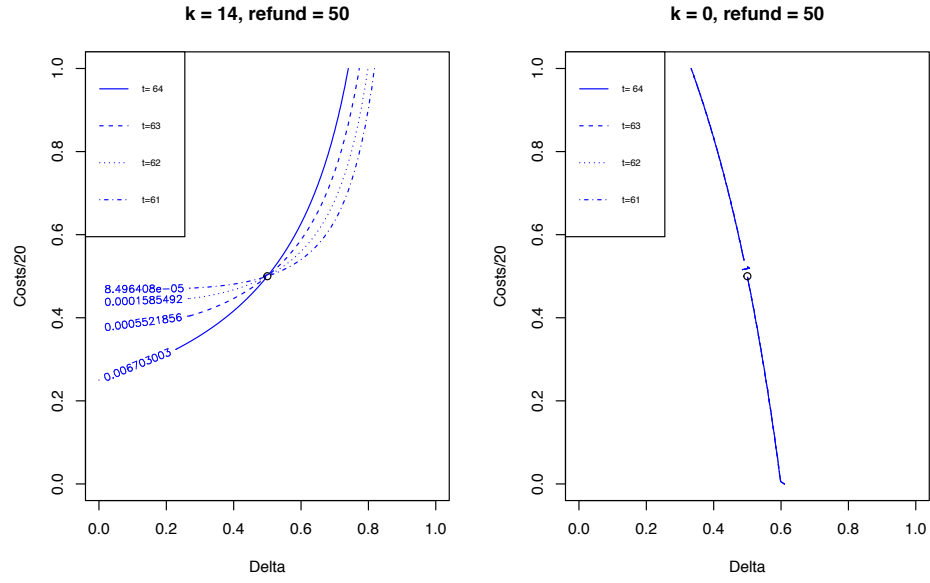


Figure A11: $p(1_{it}|1_{it}, b_i)$ Level Curves, $\delta = 0.535, c = 10$

Hence, differential direct deposit use, which generates differences in k , delivers additional identifying variation.

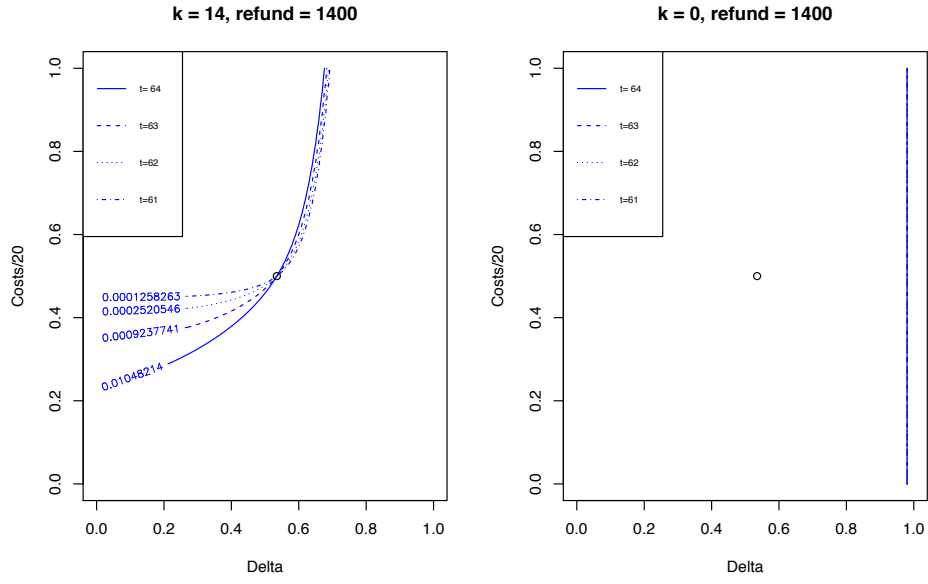


Figure A12: $p(1_{it}|1_{it}, b_i)$ Level Curves, $\delta = 0.535, c = 10$

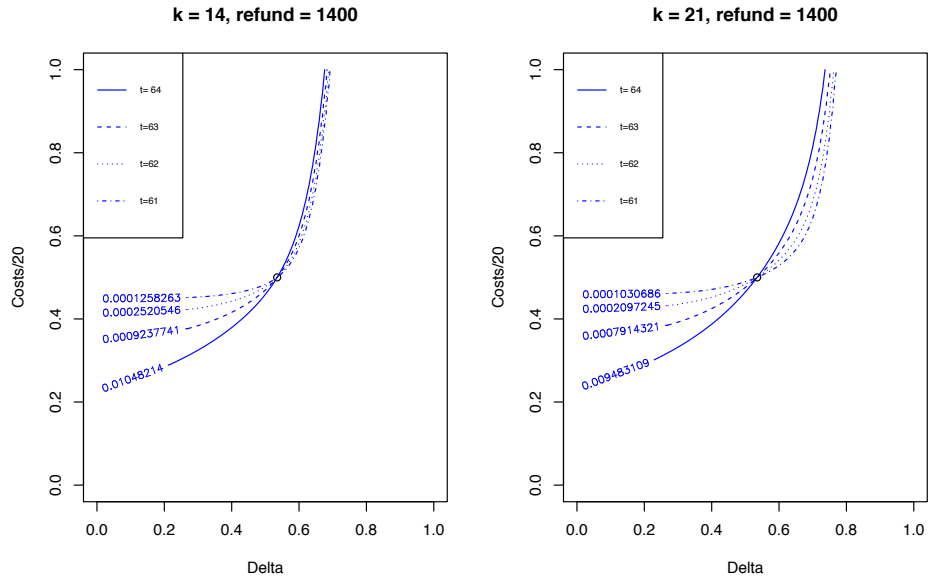


Figure A13: $p(1_{it}|1_{it}, b_i)$ Level Curves, $\delta = 0.535, c = 10$

A.3 Naive $\beta - \delta$ derivation

Recall the Euler equation for the dynamically consistent agent:

$$V_{it}(x_{it}, \epsilon_{it}) = \max_{a_{it}} [(\delta^k b - c)a_{it} + \epsilon_{it}(a_{it}) + \delta E[V_{i,t+1}(x_{i,t+1}, \epsilon_{i,t+1})|x_{it}, a_{it}]]$$

Since, the naive present-biased agent believes he will act dynamically consistently in all future periods we may write his current period maximization problem as:

$$W_{it}(x_{it}, \epsilon_{it}) = \max_{a_{it}} [(\beta \delta^k b - c)a_{it} + \epsilon_{it}(a_{it}) + \beta \delta E[V_{i,t+1}(x_{i,t+1}, \epsilon_{i,t+1})|x_{it}, a_{it}]]$$

Recall that the *ex-ante* value function, $\bar{V}_{it}(x_{it})$, is obtained by integrating over the possible realizations of shocks:

$$\bar{V}_{it}(x_{it}) \equiv \int V_{it}(x_{it}, \epsilon_{it}) g(\epsilon_{it}) d\epsilon_{it}$$

We additionally define the conditional value function $w_{it}(x_{it}, a_{it})$ as the present discounted value (net of the shocks ϵ_{it}) of choosing a_{it} and behaving optimally from period $t + 1$ on as

$$w_{it}(x_{it}, a_{it}) \equiv (\beta \delta^k b - c)a_{it} + \beta \delta \int \bar{V}_{i,t+1}(x_{i,t+1}) f(x_{i,t+1}|x_{it}, a_{it}) dx_{i,t+1}.$$

The optimal decision rule at time t solves

$$\alpha_{it}(x_{it}, \epsilon_{it}) = \arg \max_{a_{it}} w_{it}(x_{it}, a_{it}) + \epsilon_{it}(a_{it}).$$

Type-1 Extreme Value Errors

Following the logic of static discrete choice problems, the probability of observing an action a_{it} conditional on x_{it} is found by integrating out ϵ_{it} from the optimal decision rule.

$$\begin{aligned} p(a_{it}|x_{it}) &= \int \mathbf{1}[\alpha_{it}(x_{it}, \epsilon_{it}) = a_{it}] g(\epsilon_{it}) d\epsilon_{it} \\ &= \int \mathbf{1}[\arg \max_{a_{it}} w_{it}(x_{it}, a_{it}) + \epsilon_{it}(a_{it}) = a_{it}] g(\epsilon_{it}) d\epsilon_{it} \end{aligned}$$

Hence, if we are able to form the conditional value function $v_{it}(x_{it}, a_{it})$, standard methods can be applied.

In order to obtain a closed form solution for choice probabilities, we assume type-1 extreme value distributions leading to the dynamic logit model. The probability of an arbitrary choice a_{it} is given by

$$p(a_{it}|x_{it}) = \frac{\exp(w_{it}(x_{it}, a_{it}))}{\sum_{a'_{it}} \exp(w_{it}(x_{it}, a'_{it}))}.$$

Or,

$$p(a_{it}|x_{it}) = \frac{1}{\sum_{a'_{it}} \exp(w_{it}(x_{it}, a'_{it}) - w_{it}(x_{it}, a_{it}))}.$$

Importantly, under the above distributional assumption we also have the ex-ante value function in closed form.

$$\bar{V}_{it}(x_{it}) = \ln \left[\sum_{a'_{it}} \exp(v_{it}(x_{it}, a'_{it})) \right].$$

Using the observation by Hotz and Miller (1993):

$$\begin{aligned} \bar{V}_{it}(x_{it}) &= \ln \left[\sum_{a'_{it}} \exp(v_{it}(x_{it}, a'_{it})) \right] \\ \bar{V}_{it}(x_{it}) &= \ln \left[\exp(v_{it}(x_{it}, a_{it}^*)) \frac{\sum_{a'_{it}} \exp(v_{it}(x_{it}, a'_{it}))}{\exp(v_{it}(x_{it}, a_{it}^*))} \right] \\ \bar{V}_{it}(x_{it}) &= -\ln[p(a_{it}^*|x_{it})] + v_{it}(x_{it}, a_{it}^*) \end{aligned}$$

for some arbitrary action taken at time t , a_{it}^* . This expresses the ex-ante value of being at a given state as the conditional value of taking an arbitrary action adjusted for a penalty that the arbitrary action might not be optimal. We can substitute this in to our equation for the conditional value function to obtain

$$w_{it}(x_{it}, a_{it}) = (\beta\delta^k b - c)a_{it} + \beta\delta \int (v_{i,t+1}(x_{i,t+1}, a_{i,t+1}^*) - \ln[p(a_{i,t+1}^*|x_{i,t+1})])f(x_{i,t+1}|x_{it}, a_{it})dx_{i,t+1}$$

Recognizing that:

$$w_{it}(1, b_i, 1) = \beta \delta^k b_i - c$$

$$w_{it}(1, b_i, 0) = \beta \delta^{k+1} b_i - \beta \delta c - \beta \delta \ln[p(1|x_{i,t+1})]$$

We get:

$$p(1|x_{it}) = \frac{1}{1 + \exp[\beta(\delta^{k+1} - \delta^k)b - (\beta\delta - 1)c - \beta\delta \ln(p(1|1_{i,t+1}, b_i))]}.$$

B IRS Announcement of H.R. 5140



Economic Stimulus Payment Notice

Dear Taxpayer:

We are pleased to inform you that the United States Congress passed and President George W. Bush signed into law the Economic Stimulus Act of 2008, which provides for economic stimulus payments to be made to over 130 million American households. Under this new law, you may be entitled to a payment of up to \$600 (\$1,200 if filing a joint return), plus additional amounts for each qualifying child.

We are sending this notice to let you know that based on this new law the IRS will begin sending the one-time payments starting in May. To receive a payment in 2008, individuals who qualify will not have to do anything more than file a 2007 tax return. The IRS will determine eligibility, figure the amount, and send the payment. This payment should not be confused with any 2007 income tax refund that is owed to you by the federal government. Income tax refunds for 2007 will be made separately from this one-time payment.

For individuals who normally do not have to file a tax return, the new law provides for payments to individuals who have a total of \$3,000 or more in earned income, Social Security benefits, and/or certain veterans' payments. Those individuals should file a tax return for 2007 to receive a payment in 2008.

Individuals who qualify may receive as much as \$600 (\$1,200 if married filing jointly). Even if you pay no income tax but have a total of \$3,000 or more in earned income, Social Security benefits, and/or certain veterans' payments, you may receive a payment of \$300 (\$600 if married filing jointly).

In addition, individuals eligible for payments may also receive an additional amount of \$300 for each child qualifying for the child tax credit.

For taxpayers with adjusted gross income (AGI) of more than \$75,000 (or more than \$150,000 if married filing jointly), the payment will be reduced or phased out completely.

To qualify for the payment, an individual, spouse, and any qualifying child must have a valid Social Security number. In addition, individuals cannot receive a payment if they can be claimed as a dependent of another taxpayer or they filed a 2007 Form 1040NR, 1040NR-EZ, 1040-PR, or 1040-SS.

All individuals receiving payments will receive a notice and additional information shortly before the payment is made. In the meantime, for additional information, please visit the IRS website at www.irs.gov.

C Excerpts from Technical Explanation of H.R. 5140

C.1 Explanation of Provision

C.1.1 In general

The provision includes a recovery rebate credit for 2008 which is refundable. The credit mechanism (and the issuance of checks described below) is intended to deliver an expedited fiscal stimulus to the economy.

The credit is computed with two components in the following manner.

C.1.2 Basic credit

Eligible individuals receive a basic credit (for the first taxable year beginning) in 2008 equal to the greater of the following:

- Net income tax liability not to exceed 600(1,200 in the case of a joint return).
- 300(600 in the case of a joint return) if: (1) the eligible individual has qualifying income of at least 3,000; or (2) *the eligible individual has a net income tax liability of at least 1* and gross income greater than the sum of the applicable basic standard deduction amount and one personal exemption (two personal exemptions for a joint return).

An eligible individual is any individual other than: (1) a nonresident alien; (2) an estate or trust; or (3) a dependent. For these purposes, “net income tax liability” means the excess of the sum of the individual’s regular tax liability and alternative minimum tax over the sum of all nonrefundable credits (other than the child credit). Net income tax liability as determined for these purposes is not reduced by the credit added by this provision or any credit which is refundable under present law. Qualifying income is the sum of the eligible individual’s: (a) earned income; (b) social security benefits (within the meaning of sec. 86(d)); and (c) veteran’s payments (under Chapters 11, 13, or 15 of title 38 of the U. S. Code). The definition of earned income has the same meaning as used in the

earned income credit except that it includes certain combat pay and does not include net earnings from self-employment which are not taken into account in computing taxable income.

C.1.3 Qualifying child credit

If an individual is eligible for any amount of the basic credit the individual also may be eligible for a qualifying child credit. The qualifying child credit equals \$300 for each qualifying child of such individual. For these purposes, the child credit definition of qualifying child applies.

C.1.4 Limitation based on gross income

The amount of the credit (i.e., the sum of the amounts of the basic credit and the qualifying child credit) is phased out at a rate of five percent of adjusted gross income above certain income levels. The beginning point of this phase-out range is \$75,000 of adjusted gross income (\$150,000 in the case of joint returns).

C.1.5 Examples of rebate determination

Example 1. - The amount of the credit (i.e., the sum of the amounts of the basic credit and the qualifying child credit) is phased out at a rate of five percent of adjusted gross income above certain income levels. The beginning point of this phase-out range is 75,000 *of adjusted gross income* (150,000 in the case of joint returns).

Example 6. - A married taxpayer filing jointly has \$175,000 in earned income, two qualifying children, and a net tax liability of \$31,189 (the taxpayer's actual liability after the child credit also is \$31,189 as the joint income is too high to qualify). The taxpayer meets the qualifying income test and the net tax liability test. The taxpayer will, in the absence of the rebate phase-out provision, receive a rebate of \$1,800, comprising \$1,200 (greater of \$600 or net tax liability not to exceed \$1,200), and \$300 per child. The phase-out provision reduces the total rebate amount by five percent of the amount by which the taxpayer's adjusted gross income exceeds \$150,000. Five percent of \$25,000 (\$175,000 minus \$150,000) equals \$1,250. The taxpayer's rebate is thus \$1,800 minus \$1,250, or \$550.

D Instructions



2008 BOSTON EITC CAMPAIGN RAFFLE QUESTIONS

The following questions are asked for research purposes only. We will never share your personal information with any organization or its representatives. Please note that any winnings may be taxable.

- Use a No. 2 pencil only.
- Do not use ink, ballpoint or felt tip pens.
- Make solid marks that fill the oval completely
- Erase cleanly any marks you wish to change
- Make no stray marks on this form
- Do not fold, tear or mutilate this form

As a tax filer at this Volunteer Income Tax Assistance site you are automatically entered in a raffle in which you could win up to \$50. Just follow the directions below:

How It Works:

In the boxes below you are asked to choose between smaller payments closer to today and larger payments further in the future. For each row, choose one payment: either the smaller, sooner payment or the later, larger payment. When you return this completed form, you will receive a raffle ticket. If you are a winner, the raffle ticket will have a number on it from 1 to 22. These numbers correspond to the numbered choices below. You will be paid your chosen payment. The choices you make could mean a difference in payment of more than \$35, so ... CHOOSE CAREFULLY!!!

RED BLOCK (Numbers 1 through 7) : Decide between payment today and payment in one month

BLACK BLOCK (Numbers 8 through 15): Decide between payment today and payment in six months

BLUE BLOCK (Numbers 16 through 22): Decide between payment in six months and payment in seven months

Rules and Eligibility:

For each possible number below, state whether you would like the earlier, smaller payment or the later, larger payment. Only completed raffle forms are eligible for the raffle.

All prizes will be sent to you by normal mail and will be paid by money order. One out of ten raffle tickets will be a winner. You can obtain your raffle ticket as soon as your tax filing is complete. You may not participate in the raffle if you are associated with the EITC campaign (volunteer, business associate, etc.) or an employee (or relative of an employee) of the Federal Reserve Bank of Boston or the Federal Reserve System.

TODAY VS. ONE MONTH FROM TODAY

WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 1 AND 7?

Decide for **each** possible number if you would like the smaller payment for sure today or the larger payment for sure in one month? Please answer for each possible number (1) through (7) by filling in one box for each possible number.

Example: If you prefer \$49 today in Question 1 mark as follows: ☒ \$49 today or ☐ \$50 in one month
If you prefer \$50 in one month in Question 1, mark as follows: ☐ \$49 today or ☒ \$50 in one month

If you get number (1): Would you like to receive ☐ \$49 **today** or ☐ \$50 in **one month**

If you get number (2): Would you like to receive ☐ \$47 **today** or ☐ \$50 in **one month**

If you get number (3): Would you like to receive ☐ \$44 **today** or ☐ \$50 in **one month**

If you get number (4): Would you like to receive ☐ \$40 **today** or ☐ \$50 in **one month**

If you get number (5): Would you like to receive ☐ \$35 **today** or ☐ \$50 in **one month**

If you get number (6): Would you like to receive ☐ \$29 **today** or ☐ \$50 in **one month**

If you get number (7): Would you like to receive ☐ \$22 **today** or ☐ \$50 in **one month**

TODAY VS. SIX MONTHS FROM TODAY

WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 8 AND 15?

Now, decide for **each** possible number if you would like the smaller payment for sure **today** or the larger payment for sure in **six months**? Please answer each possible number (8) through (15) by filling in one box for each possible number.

If you get number (8): Would you like to receive ☐ \$49 **today** or ☐ \$50 in **six months**

If you get number (9): Would you like to receive ☐ \$47 **today** or ☐ \$50 in **six months**

If you get number (10): Would you like to receive ☐ \$44 **today** or ☐ \$50 in **six months**

If you get number (11): Would you like to receive ☐ \$40 **today** or ☐ \$50 in **six months**

If you get number (12): Would you like to receive ☐ \$35 **today** or ☐ \$50 in **six months**

If you get number (13): Would you like to receive ☐ \$29 **today** or ☐ \$50 in **six months**

If you get number (14): Would you like to receive ☐ \$22 **today** or ☐ \$50 in **six months**

If you get number (15): Would you like to receive ☐ \$14 **today** or ☐ \$50 in **six months**

SIX MONTHS FROM TODAY VS. SEVEN MONTHS FROM TODAY

WHAT WILL YOU DO IF YOU GET A NUMBER BETWEEN 16 AND 22?

Decide for **each** possible number if you would like the smaller payment for sure **in six months** or the larger payment for sure **in seven months**? Please answer for each possible number (16) through (22) by filling in one box for each possible number.

If you get number (16): Would you like to receive ☐ \$49 **in six months** or ☐ \$50 **in seven months**

If you get number (17): Would you like to receive ☐ \$47 **in six months** or ☐ \$50 **in seven months**

If you get number (18): Would you like to receive ☐ \$44 **in six months** or ☐ \$50 **in seven months**

If you get number (19): Would you like to receive ☐ \$40 **in six months** or ☐ \$50 **in seven months**

If you get number (20): Would you like to receive ☐ \$35 **in six months** or ☐ \$50 **in seven months**

If you get number (21): Would you like to receive ☐ \$29 **in six months** or ☐ \$50 **in seven months**

If you get number (22): Would you like to receive ☐ \$22 **in six months** or ☐ \$50 **in seven months**